DISTRIBUTED PARKING SPOT DETECTION WITH ON-BOARD SENSORS

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By

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DISTRIBUTED PARKING SPOT DETECTION WITH ON-BOARD SENSORS

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SUMMARY

Drivers searching for parking are significant contributors to congestion in urban areas. It has been shown that informing these drivers about available parking can help alleviate some of this congestion and thus reduce overall travel time and emissions. However, informing drivers about available parking requires up-to-date knowledge of the occupancy of parking spaces in the area. For certain situations with well-controlled entries and exits, like parking garages, this is a simple process. For more distributed parking, as in open parking lots or curbside parking, the current approach is to deploy sensors at each individual parking space.

A more dynamic occupancy detection system may be possible using vehicle-borne sensors to check for open spaces. As vehicle technology continues to advance, capable sensors may even be natively equipped on some vehicles and trim levels, with no need for aftermarket kits. However, when using sensors that make distance measurements to determine whether or not a space is open, a secondary system must be able to check that a detected opening is a parking space and not an intersection or a bus stop or other area that cannot be parked in.

In this thesis, a method for detecting openings using a late-model vehicle's ultrasound parallel park assist sensors and then verifying that the openings are valid parking using basic map data in OpenStreetMap is described. An overview of parking guidance systems as well as relevant sensors is also provided. The system is then tested in two stages, first for the ultrasound sensors by themselves and then for the combined detection and validation system in three different parking scenarios around Atlanta.

Results show that the system is effective at identifying opening parking spaces both on the street and in parking lots, though parking lots with angled spots and GPS accuracy are both challenges for the system.

CHAPTER 1

INTRODUCTION

1.1 – The Costs of Searching for Parking

According to the 2015 version of the Urban Mobility Scorecard periodically published by the Texas A&M Transportation Institute, traffic congestion in the United States is by almost any measure at an all-time high. While the 2007-2008 financial crisis and ensuing recession did serve to draw down congestion for several years, by 2012 total wasted fuel (additional fuel consumption due to congestion) reached 3 billion gallons for the first time as total time of delay also hit a record high of 6.7 billion hours. In 2014, those had further increased to 3.1 billion gallons and 6.9 billion hours, for a total cost of $160 billion. Put in terms of individual commuters, this is 19 gallons of fuel and 42 hours wasted per commuter over the course of the year. They further project that by 2020, wastes will be 3.8 billion gallons and 8.3 billion hours for a cost of $192 billion (2014 dollars) (Schrank, Eisele, Lomax, & Bak, 2015).

The data used by Schrank et al. mainly incorporate vehicle travel speeds, volumes, and occupancies without considering the purpose of travel for individual vehicles, but other studies have also examined why particular drivers are on the road. A paper published by Shoup in 2006 reviewed multiple other studies from various points in the 20th century and found that on average 30% of traffic in urban areas was "cruising" for curb parking, with 8.1 minutes of average search time (Shoup, 2006). Shoup's paper exclusively looked at curbside parking, which is often cheaper or even free and therefore more desirable than relatively more expensive off-street parking, even if the off-street parking is readily available. However, at some times of day or in certain areas or events even off-street parking may not be readily available, and in those cases congestion would rise even further with the greater number of cruising parking searchers. In one example provided by Shoup, cruising in a commercial district in Los Angeles with 470 curbside parking spaces and high turnover (averaging 17 cars per spot per day) creates 3500 additional vehicle miles traveled (VMT) and 440 additional hours of travel every day (Shoup, 2006). Even if we assume this traffic level only for weekdays, this comes to 910000 VMT and 114400 hours for one year – all for an area with fewer than 500 parking spaces. Clearly, drivers searching for parking contribute significantly to overall congestion levels and total vehicle miles traveled (VMT) in urban areas. Helping drivers find parking spaces more quickly would be directly beneficial to both municipalities and individual drivers themselves, in terms of reduced direct fuel costs, time saved, and emissions reduced.

1.2 – Collecting Data for Parking Guidance

The US Federal Highway Administration has found that providing more information and direction to drivers looking for parking is an effective method for reducing traffic congestion and delays. This has been shown in situations ranging from airport parking garages in Baltimore to street parking in San Francisco to special event parking in St. Paul (Paniati, 2007). However, providing accurate information to drivers requires up-to-date information on the occupancy of parking spots in nearby parking areas. Collecting this information is simple and inexpensive in certain scenarios: for example, in parking garages and controlled lots counting the number of entries and exits allows calculation of net available spots at any time. More dispersed parking, particularly curbside parking, usually requires an occupancy sensor for each individual parking spot. These sensors usually cost between $250 and $800, with retrofits being more expensive than inclusion with new construction (Paniati, 2007).

Rather than relying on static sensors, vehicle-based sensors may be able to aid in parking occupancy measurements at these more dispersed locations. A team from Rutgers University in 2010 described a possible "ParkNet" method using taxicabs with ultrasound sensor kits to check occupancy in curbside parking spots (Mathur et al., 2010). However, whenever using simple range detection sensors for dynamic occupancy detection, care must be taken that observed openings are actually parking spots and not invalid openings where parking may be illegal (e.g., a bus stop on a street with curbside parking). The ParkNet team suggested that this problem be solved by creating a database of all curbside parking spot locations and using a GPS sensor to check detected openings against the legal parking locations (Mathur et al., 2010).

1.3 – Thesis Organization

In this thesis, we will briefly review current parking guidance systems and their methods of parking occupancy data collection. We will then present a method for occupancy data collection using vehicle-integrated ultrasound sensors and GPS receivers to perform opening detection and location. In addition, we detail a method for discerning the validity as parking of detected openings, using publicly available, open-source mapping data but requiring no specific knowledge of individual parking spot locations.

We also describe an evaluation of a mobile parking occupancy detection system combining both methods, using real parking lots and curbside parking in and around the campus of the Georgia Institute of Technology in Atlanta, Georgia. This evaluation attempts to answer questions about the technical capabilities and limits of the ultrasound and GPS systems. The map data and algorithms used to confirm parking spot validity are also tested in various scenarios to determine where they are or are not sufficient to make an accurate determination, and improved or alternate methods of spot validation are considered.

Chapter 2 provides a literature review of current parking guidance systems, focusing on both their overall efficacy and on method of occupancy data collection. A background of automotive ultrasound and GPS systems and parking representation in map data is given in Chapter 3, along with specific elements relevant to the vehicle and map database used for our implementation. Methods for data collection, open spot detection, and open spot validation as available parking are described in Chapter 4. Chapter 5 details both the testing procedure for the system and the outcomes of the tests. Chapter 6 discusses these results, potential solutions to any problems discovered in testing, prospective implementations for fleet-wide systems, and relevant future work to further improve parking-related traffic issues.

CHAPTER 2

LITERATURE REVIEW

In this chapter, we will examine the development and current status of parking guidance systems both in practice and in literature. We will also propose a new approach to collecting data for parking guidance systems.

2.1 – Parking Guidance Systems

Modern work on parking availability and driver decision-making is heavily model-based and often treated within the context of the larger field of traffic pattern modeling. Early work used logit models for driver choice, examining the effects of parking availability, cost of parking, walking time from final destination, parking type (garage or on-street), and purpose of travel on final parking spot selection (Van der Goot, 1982).

As technology has progressed, engineers have worked to keep drivers better informed and more precisely directed to minimize confusion and streamline traffic patterns as more and more vehicles fill the roads. Recent modeling efforts include new Intelligent Transportation Systems (ITS) and have sought to understand how they might be used to influence driver behavior and choice in positive ways. Advanced Parking Management Systems (APMS) and in particular Parking Guidance Information (PGI) systems, which provide direction and information to drivers to help with their parking searches, are increasingly common methods for driver management. Signs such as those in figure 2.1 are one common type of PGI system, informing drivers of both parking location and availability. A 2001 study by Waterson, Hounsell, and Chatterjee built a sign-based PGI model and incorporated it into a larger traffic model for a generic city similar to Southampton, and found a reduction in travel times, albeit a minimal one (Waterson, Hounsell, & Chatterjee, 2001). However, a separate study by Thompson, Takada, and Kobayakawa that same year developed a genetic algorithm optimization model for the best way to deploy PGI equipment, and was able to minimize both VMT and queue lengths at garage entrances (Thompson, Takada, & Kobayakawa, 2001). In 2007, a review of US APMS by the Federal Highway Administration found that the systems were effective in a variety of applications, improving traffic flow and customer satisfaction at the Baltimore-Washington International Airport (BWI), encouraging better utilization of public transit in San Francisco, and even reducing delay while increasing total traffic volume through a large intersection preceding a nearby special event (Paniati, 2007).

Some APMS approach the congestion problem slightly more indirectly, influencing drivers by adjusting the price of parking rather than attempting to tell them where to go. Partially in response to Shoup, Arnott and Inci developed a model that suggested raising the price of on-street parking "to the point where cruising for parking is eliminated without parking becoming unsaturated," (Arnott & Inci, 2006). This was tested in practice by San Francisco with the SF*park* project, begun in 2011, which adjusted street parking prices 10 times in the first 2 years of the project. In these two years the project was effective at moving parking space occupancy levels towards the target 60% - 80% range as well as reducing cruising by an estimated 50% (Millard-Ball, Weinberger, & Hampshire, 2014). If data can be obtained more quickly or in near real-time, further optimization is possible: Mackowski, Bai, and Ouyang described a dynamic pricing model capable of incorporating real-time data to update parking prices every fifteen minutes to maintain parking garages at 85% or below occupancy levels, which they found sufficient to minimize circling for parking (Mackowski, Bai, & Ouyang, 2015). Other recent work has also begun to investigate the impact of related emerging systems and technologies, such as a study by that found free-floating vehicles in a carsharing program could make more efficient use of parking spaces than private vehicles when combined with the appropriate parking pricing schemes (Balac, Ciari, & Axhausen, 2017).

Whether by influencing driver behavior with PGI systems or dynamic parking pricing schemes, it is possible to reduce the number of drivers cruising for parking and the associated time lost and added emission. However, doing so often relies on accurate and up-to-date information on current parking occupancy levels. Dynamic pricing has been done with historical baseline data in the past, as with the SF*park* project (Millard-Ball et al., 2014) but can certainly benefit from real-time data as well (Mackowski et al., 2015). PGI systems in most current implementations almost always require real-time data to function properly (there are some exceptions; in January of 2017 Google Maps added a vague, historical data-based "parking difficulty" indicator to its mobile application so that drivers could plan for extra search or walking time accordingly (Albertson, 2017)).

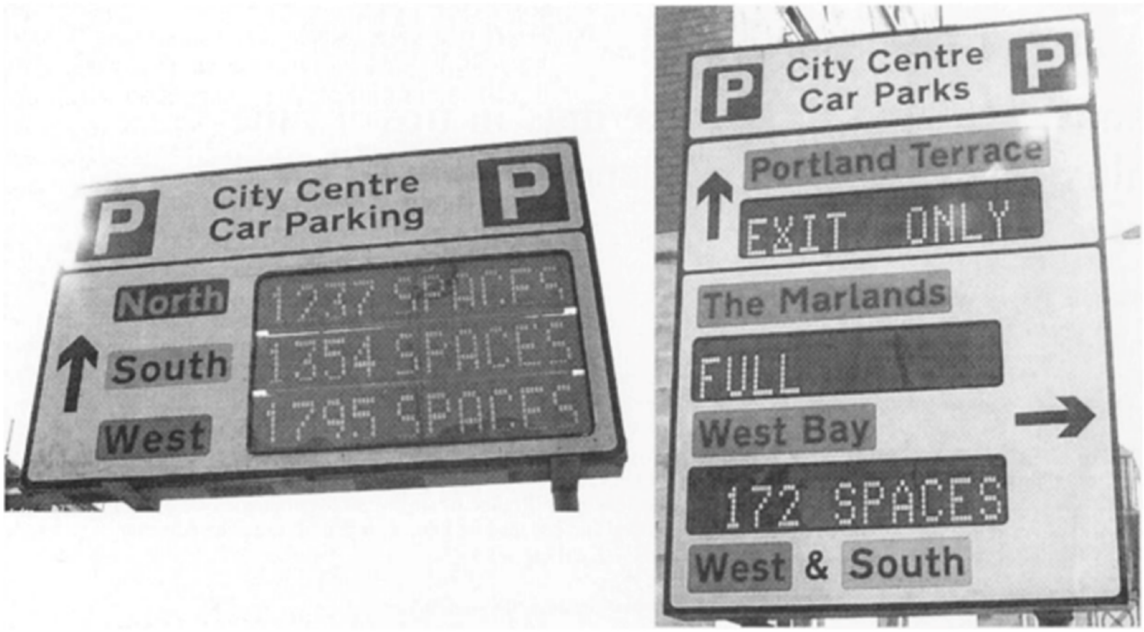

Figure 2.1: Parking guidance information signs for urban parking garages (Waterson et al., 2001).

2.2 – Current Data Collection for APMS/PGI

Most current approaches to parking occupancy data collection for use with APMS or PGI systems can be separated into two categories. If the parking is in a lot or garage where all entrances and exits are fixed, sensors can be placed at these locations to keep track of the number of vehicles entering and exiting as seen in figure 2.2. Sensor type can vary, from induction loops to ultrasound sensors to simple video detection. The net number of entries can then be compared to the total number of parking spots to give the occupancy. For other parking spot distributions, however, access to the parking area may not be sufficiently restricted for an entry/exit counting method to work. In these cases – notably including all street parking – an occupancy determination method is required for each individual parking spot. This requires the placement of a sensor (again usually ultrasound or electromagnetic) at each spot (Paniati, 2007). Parkeon's deployment of sensors connected to a central control and payment kiosk in Washington, DC in 2010 was an early implementation of this for a street parking environment (Halsey, 2010). Single-spot sensors are sometimes also used within parking garages: ParkHelp's commercially available Parking Guidance System utilizes an ultrasound sensor above each space, combined with a red/green indicator LED to speed spot location for drivers within garages (ParkHelp, 2017).

System deployment is clearly more complex and usually more expensive in the individual sensor case, even as information for on-street parking occupancy levels is often the more valuable for reducing the number of cars cruising for on-street parking. The US FHWA estimates per-spot costs for APMS deployment at $250 to $800. In the specific case of the BWI airport, which used ultrasound sensors to individually monitor occupancy of over 13,000 spots, the per-spot cost was $450. It was estimated that a retrofit of the same system on an existing garage would have been more expensive, due to the need for extra power and communication conduits to the sensors for each space (Paniati, 2007). For some context, Chicago has about 35,000 metered street parking spaces, and San Francisco has about 24,000 (Transportation Alternatives, 2008). Using the low-end per-spot cost estimate, that comes to $8.75 million and $6 million, respectively, to put a sensor at each spot; for the high-end estimate the costs would be $28 million and $19.2 million. Also, as Mathur et al. point out, if street parking is available but individual spots are not marked, then proper sensor placement becomes difficult because the position of parked cars is unknown (Mathur et al., 2010).

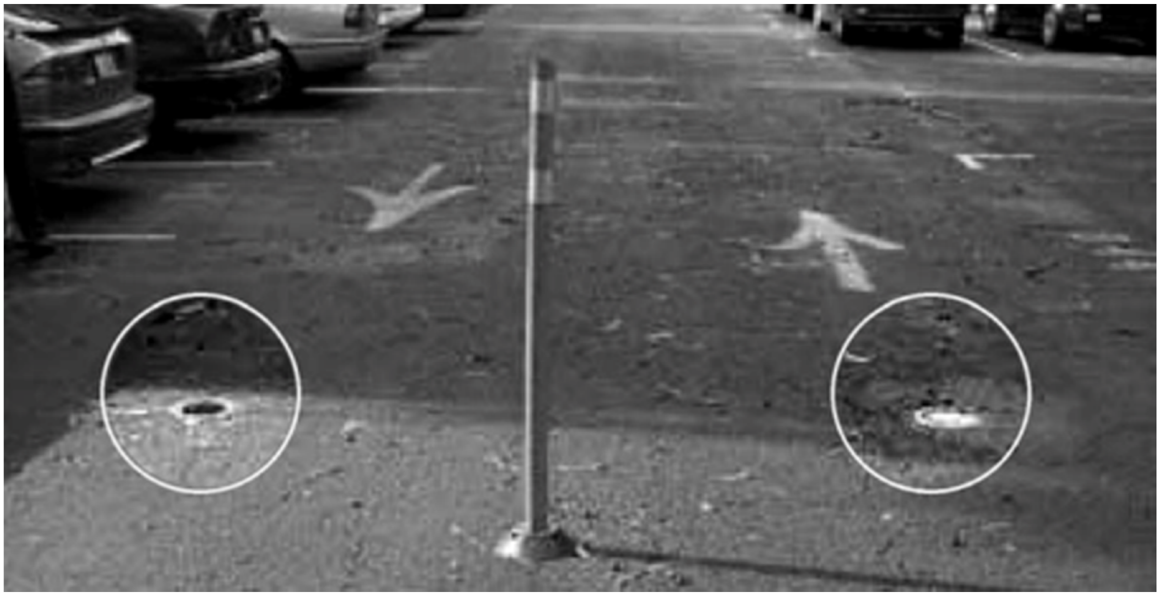

Figure 2.2: Ultrasound sensors embedded in asphalt tracking entries and exits to a parking lot (Paniati, 2007).

2.3 – Proposed Data Collection for APMS/PGI

Current parking occupancy data collection systems are either limited to monitoring controlled areas or expensive and tedious to deploy individually to various parking spaces. The ParkNet system proposed by Mathur et al. has raised the possibility of a third method of data collection: vehicle-mounted sensors. Such sensors while individually perhaps as expensive as stationary single-spot sensors (Mathur et al. estimate a $400 cost for a complete vehicle sensor system) would be able to scan a large number of parking spots quickly, whether those spots be street parking or in a parking lot (Mathur et al., 2010). Furthermore, as technology included on vehicles diversifies and spreads, these sensor systems may not even need to be added separately but rather use data from sensors intended for other purposes already on the vehicle. Similarly, Ford Motor Company in 2016 showcased several mobile applications designed to help with parking availability. One, the "Parking Spotter" project, aims to use vehicle sensors to detect openings with a map of known parking spot locations (Ford Motor Company, 2016). Another, the “GoPark” project, plans to incorporate both historical and real-time data and pattern analysis in partnership with IBM to make predictions about where parking is most likely present (Stinson, 2016). However, none of these systems are functional without detailed spot-by-spot location data against which to compare their sensor data.

In this work, we use the stock on-board parking assist ultrasound sensors and GPS in an unmodified, late-model passenger vehicle to detect available parking spots. We examine the processing of the raw ultrasound signals to detect open spots, as well as developing GPS-based “situational awareness” system to confirm that detected spots are valid parking, using general map data and not requiring a detailed map of individual parking spots as previous work has suggested would be necessary.

Chapter 2 Summary

Various systems have been developed to help drivers search for parking. These systems either rely on historical trends or real-time data to either direct drivers to where parking is available, or to influence driver choice via pricing changes for curbside or lot parking. When collecting real-time data, current practice is limited to either controlled entry/exit parking lots or placing individual sensors for each parking space. Instead, we propose a vehicle-based parking space occupancy detection system, which would allow coverage of a larger number of parking spaces at lower cost. We will show this vehicle-based system to be feasible using only stock vehicle sensors and general map data.

CHAPTER 3

TECHNOLOGY DESCRIPTION

In this chapter, we will review three key technologies used in this project: automotive ultrasound and GPS sensors, and a map database. We will give a brief background for these technologies, and highlight strengths and weaknesses of each when used in our application.

3.1 – Automotive Sensors

One important goal of this project was to collect all data using only the sensors installed on the vehicle at the factory, with no aftermarket sensor kits or additions required. Data from basic vehicle speed measurements to raw ultrasound sensor feeds to GPS-based latitude and longitude points can all be acquired from the vehicle's CAN bus. This would enable implementation of a mobile parking occupancy data collection system at a fleet level with minimal installation of additional hardware, saving time and money.

Sensor technology has now arrived at a point where this is a feasible goal. Early sensors such as speedometers and tachometers simply informed drivers about the current state of their vehicles before advancing to helping them maintain control of their vehicles, with technologies such as inertial sensors and individual wheel speed sensors enabling anti-lock braking systems (ABS) and stability systems (Stiller, León, & Kruse, 2011). A combination of microprocessor-based engine control modules (ECM) and developments in microelectromechanical systems (MEMS) manufacturing converging beginning in the early 1980s have led to an explosion of sensor usage in the three general areas of "powertrain" (engine, transmission), "chassis" (steering, suspension, braking, stability), and "body" (occupant safety and comfort). A 2001 report compiled a representative but non-exhaustive list of 107 different sensor types across these three areas (Fleming, 2001); another review by the same author found an additional 60 significant developments only 7 years later (Fleming, 2008).

However, there has been another important shift in the focus of some of these sensors: instead of only monitoring the vehicle itself, they have also been turned outwards to keep track of the environment around the vehicle. Stiller, León, and Kruse identify sonar, lidar, radar, and video as being the primary sensor types to gather "information beyond the ego-vehicle state" and leading to technologies such as lane departure warning (LDW), adaptive cruise control (ACC), and automated emergency braking (AEB) (Stiller et al., 2011). Fleming breaks "distance sensors" up into long range and short range categories, with long range working from 30-100 m and short range from 0 to 30 m (Fleming, 2008). These sorts of sensors that can measure the environment around a vehicle are precisely the sort that would be useful for observing open parking spaces.

Figure 3.1 gives a summary of the general applications for various types of distance sensors. Previous work from this laboratory explored the technical aspects of the use of lidar for mapping parking lots, and with a few caveats (black cars are sometimes not detected correctly) found it to be an effective approach (Hammoud, 2015). However, while lidar kits are becoming more widely available, lidar is not as prevalent on current production vehicles as ultrasound. This work focuses on the use of native, integrated ultrasound sensors on production vehicles.

Fleming broadly characterizes automotive ultrasound sensors as having frequencies near 50 kHz and range of up to 4 m, and specifically identifies their main applications as obstacle detection while reversing and with parking assist or self-parking systems. He notes that ultrasound sensors are hampered by relatively lower update frequencies when compared to radar, lidar, or camera technologies, and like lidar and camera suffer in inclement weather. The main advantage of ultrasound sensors is in their particularly low cost. For parking assist systems, the sensors must be able to detect in front, behind, and to the sides of the vehicle, which pairs well with the back-up obstacle detection that ultrasound sensors are also often used for (Fleming, 2008).

DISTANCE SENSOR AUTOMOTIVE APPLICATIONS

Distance Sensor Application	Sense Area			Distance Sensor Technology							
X = sense areas s = secondary uses P = Primary uses	Front	Side	Rear	Long range radar	UWB radar	Multibeam radar	Laser radar	Camera Vision	Ultrasonic	Far IR (warm body)	Near IR (illumination)
Short Range Applications											
- Blind spot detection		X	X		s	P	s	P			
- Lane departure warning	X	s						P			s
- Forward collision warning [a,b]	X				P	s	P	P		s	s
- Pre-safing [a]	X	X	s		P	P	P				
- Back-up obstacle detection		s	X		s			P	P		
- Parking assist	s	X	X		s		s	P	P		
- Stop-and-go/low speed ACC	X	s			P		P	P			
Long Range Applications											
- Adaptive cruise control	X	s		P			P	s			
- Forward collision warning [a,c]	X			P			P	s		s	s
- Night vision	X	s								P	P

Sense areas and application uses are based on published literature and the judgment of the author.
[a] Also utilizes vehicle dynamics sensor inputs (braking, deceleration, etc.)
[b] Various types of short-range radars, sometimes together with camera vision, detect rapid closing rates of slower-speed vehicles with respect to nearby slow or stopped vehicles or pedestrians ahead.
[c] Various types of long-range radars detect rapid closing rates of faster-speed vehicles with respect to more distant slow or stopped vehicles ahead.

Figure 3.1: Distance sensor technology and target sensor areas for automotive applications (Fleming, 2008).

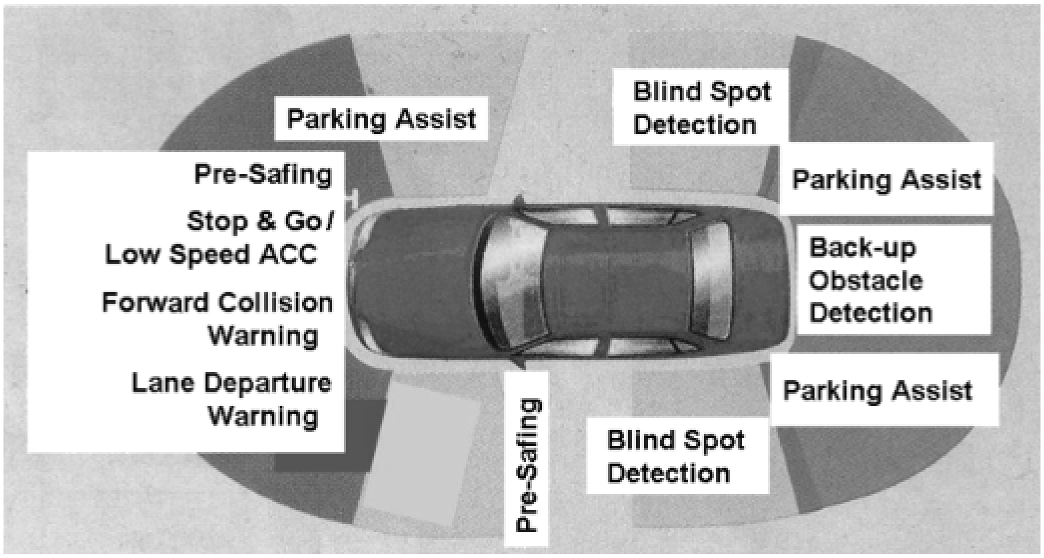

Figure 3.2: Short range distance sensor coverage areas and applications (Fleming, 2008).

Figure 3.3: Sideways-facing parking assist ultrasound sensor on lab vehicle (circled).

3.1.1 – Ultrasound Sensors for Parking Assist

As shown in figures 3.2 and 3.3, parking assist sensors must be able to “see” to the sides of the vehicle and detect open spaces there, which makes them well suited to collecting data for parking guidance systems. As previously noted, ultrasound sensors have the advantage of being relatively inexpensive, but they do suffer some limitations compared to short-range radar or cameras with machine vision. To ensure appropriate coverage, four sensors are commonly used even for simple back-up object detection (Fleming, 2008). The width of the ultrasound beam itself may also cause several issues. First, the “beam” is emitted more as an expanding cone than as something with a profile of constant width. As such it is more accurately characterized by an opening angle, meaning that the beam width when detecting objects will be dependent on how far away those objects are (Park, Kim, Seo, Kim, & Lee, 2008). This opening angle θ_0 can be calculated with equation 3.1, for speed of sound c, transducer diameter d, and center frequency of the transducer f_r. Speed of sound is temperature and humidity dependent, but 340 m/s is a commonly accepted middle-ground value for most applications. Also note that wavelength λ is equal to c divided by f_r, and this equation is often expressed in terms of λ. For a 50 kHz transducer this will generally result in a wavelength of less than one centimeter.

$$\theta_0 = \sin^{-1}\left(\frac{0.61 * c}{d * f_r}\right)$$

Equation 3.1: Ultrasound transducer opening angle calculated from transducer diameter, center frequency, and speed of sound (Park et al., 2008).

In addition, in most systems as-built there is often some uncertainty in beam opening angle which leads to uncertainty in the actual width of detected objects. While it may appear that this is correctable by moving to a narrower beam opening angle, past a certain point this will introduce multipath errors that are an even greater problem (Park et al., 2008).

The temperature and humidity dependence of the speed of sound is also a potential source of concern. Both the beam opening angle calculation and distance calculations using the time-of-flight (ToF) method require accurate knowledge of the speed of sound. The ToF calculation is very simple; for time between pulse sending and echo receiving *t* and speed of sound *c* it is, distance between sensor and object *D* is given as in equation 3.2:

$$D = \frac{t * c}{2}$$

Equation 3.2: Distance calculation by time-of-flight method (Agarwal, Murali, & Chandramouli, 2009).

Fortunately, the humidity dependence has relatively little effect when compared to the temperature dependence, and a temperature dependent speed of sound is easy to calculate. This is shown in equation 3.3 with *T* in units of degrees Celsius and velocity *c* in units of m/s (Agarwal et al., 2009):

$$c(T) = 340 * \left(1 + \frac{T}{273}\right)^{\frac{1}{2}}$$

Equation 3.3: Temperature dependent speed of sound (Agarwal et al., 2009).

Agarwal et al. further claim that a ±20 C variation in temperature results in less than a ± 10 cm variation in measured distances (Agarwal et al., 2009). This seems slightly optimistic; for a -20 C to 40 C range speed of sound varies from 327 m/s to 364 m/s. If an object 5 m distant is measured assuming *c* = 340 m/s, its observed range will vary from 5.2 m to 4.6 m. If an ambient temperature sensor can be used to update *c*, much of the uncertainty in the ToF calculations can be removed.

With the limited range and uncertainties in beam opening angle and speed of sound, it might seem that ultrasound sensors are a poor choice for parking assist systems, or for data collection on parking occupancy. However, all alternatives have other problems that can make them even less desirable. For LIDAR and laser-based systems, car color can be an issue; black cars in particular are often not detected. Camera and machine vision systems can provide more information than just distance but suffer when lanes become hard to recognize from damage to markers of from being occluded by other vehicles. Radar can be effective, though it does occasionally suffer from issues with scattering and is also far more costly (Park et al., 2008). Ultrasound sensors are thus a strong choice if accurate analyses can be made from their simple data.

Initial testing on the ultrasound sensors in our laboratory vehicle revealed two main issues that affected the accuracy of our ultrasound data, both appearing at the edges of detected vehicles and thus broadly termed "edge effects." Width distortion causes an over-representation of the length of parked vehicles and an under-representation of open lengths between parked vehicles, and scattering of the ultrasound pulse causes noisier data at the edges of parked vehicles.

3.1.1.1 – Width Distortion in Ultrasound Sensors

When trying to measure the width of open spots, the cone-shaped ultrasound beam can cause problems in taking accurate measurements. As shown in figure 3.4 and especially figure

3.4 (g), an ultrasound sensor may detect objects some distance from its centerline when detecting the edge of objects. Park et al. developed a multi-echo reading method to correct for this, as seen in figure 3.5, but our system did not have the same sort of multi-echo capability (Park et al., 2008).

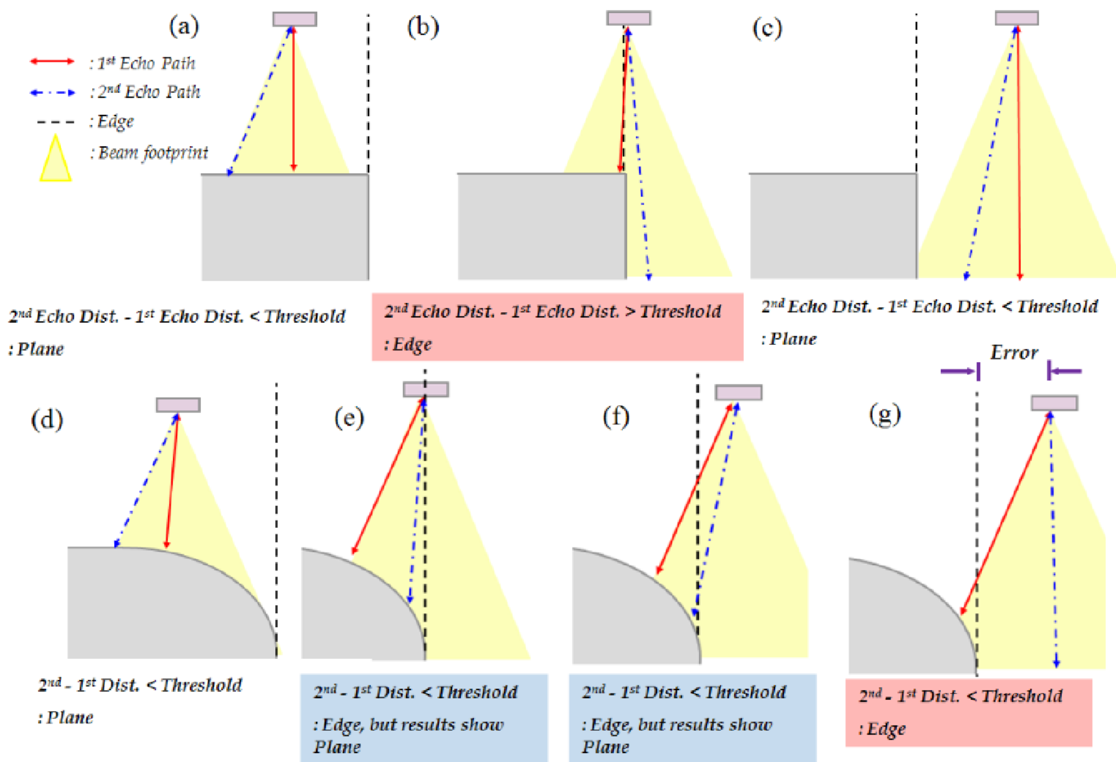

Figure 3.4: Ultrasound object detection on planar surfaces and edges (Park et al., 2008).

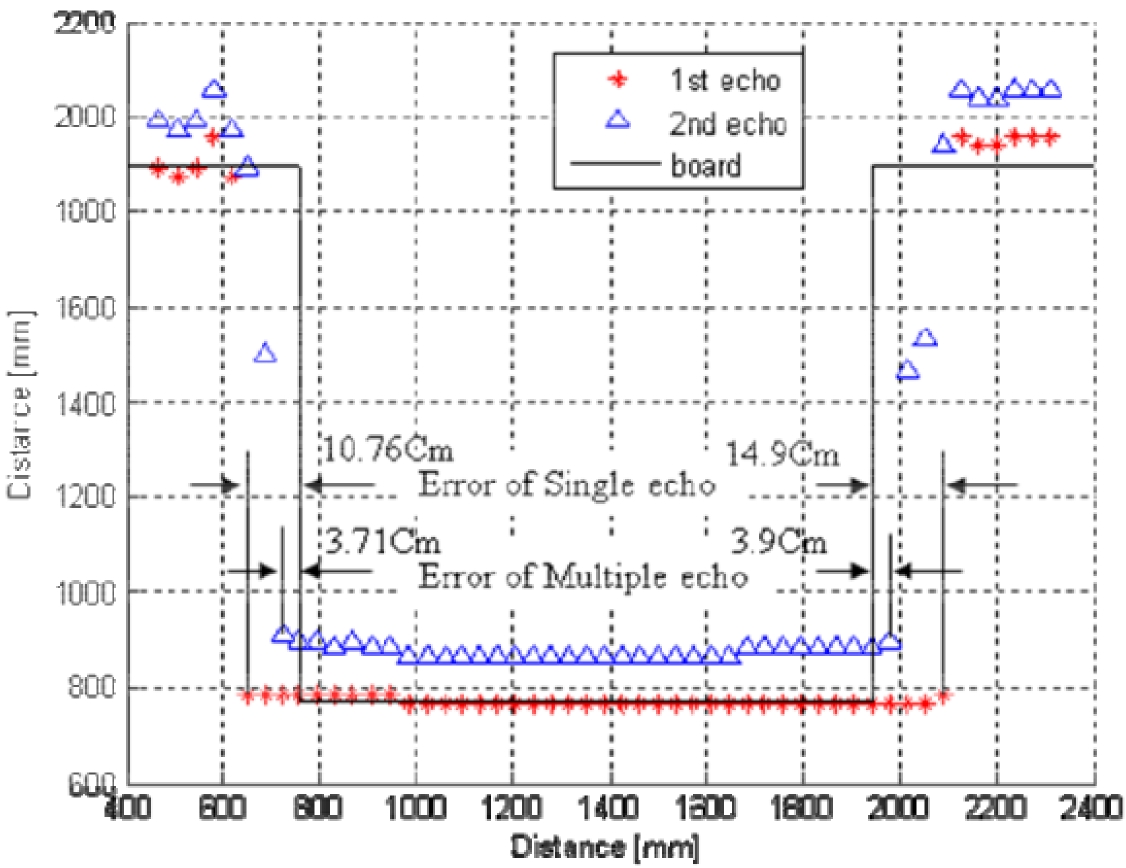

Figure 3.5: Error reduction with multiple echo technique for edge detection shown in figure 3.4 (Park et al., 2008).

In the context of parking assist sensors, which are mounted perpendicularly to a vehicle's direction of travel, the sensor may detect objects behind or forward of the sensor's location on the vehicle. This can cause over-reporting of the length of detected objects which in turn leads to under-reporting of the length of open spaces bounded by such objects, as seen in figure 3.6. The trailing edge of the ultrasound cone continues to detect the first parked vehicle after the sensor is past, and the leading edge detects the second vehicle before the sensor is parallel with it. Mathur et al. also describe this effect as seen in figure 3.7, where 3.7 (a) shows two distinct vehicles parked at a distance from each other with a clear gap, while the two more closely parked vehicles in 3.7 (b) appear to have no gap between them, even though they are not touching in reality

(Mathur et al., 2010). Because our method ultimately focused on detecting and quantifying openings between cars and not counting cars, our interest in width distortion is primarily in understanding what sorts of open length values should be considered possible parking. The initial testing described in Chapter 5 quantifies the distortion expected by our test vehicle's sensors in various scenarios.

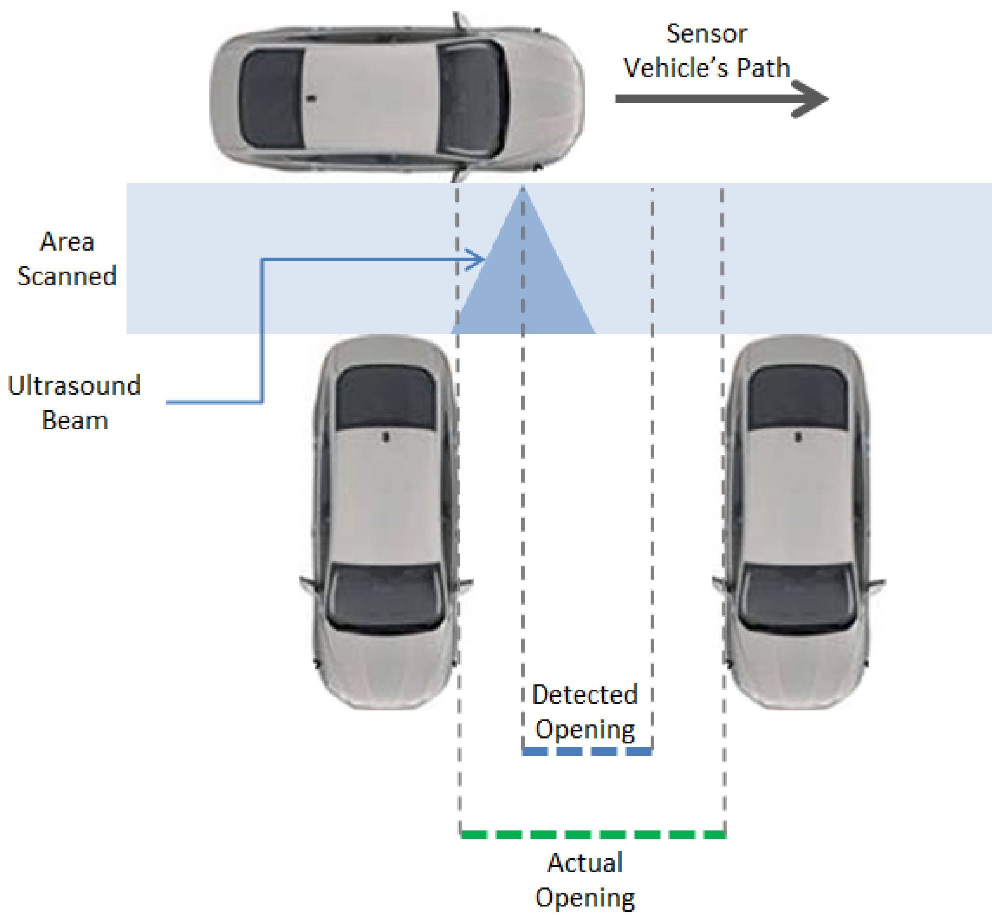

Figure 3.6: Detected versus actual openings for conical ultrasound beams.

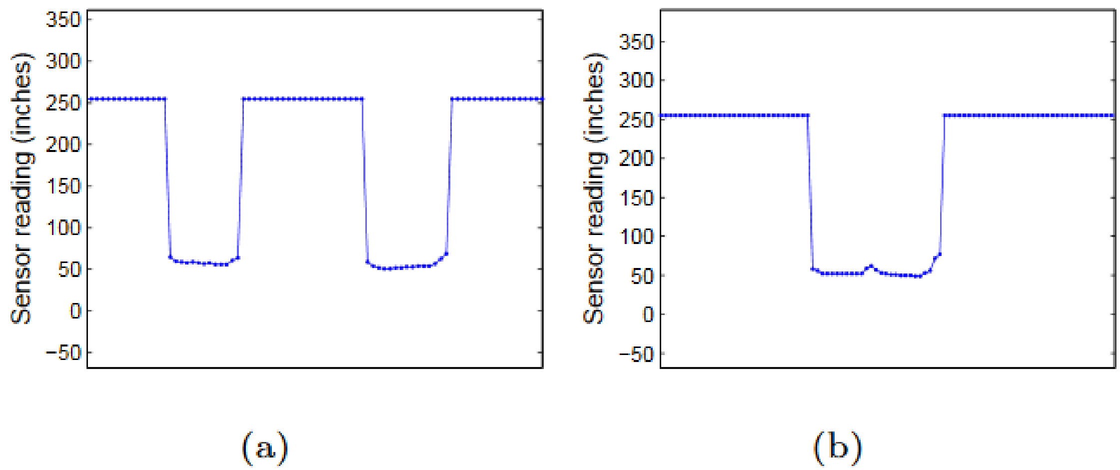

Figure 3.7: Parallel parked cars with space in between them (a) and with very little space between them (b), demonstrating blending of nearby objects from the conical ultrasound beam (Mathur et al., 2010).

3.1.2 – Vehicle GPS

The vehicle's location is determined by the integrated GPS unit. Because of the complexity of the GPS system (it bears the distinction of being one of the few applications of Einstein's theories of both special and general relativity in daily life), we will focus only issues related to GPS accuracy and precision here. For a more complete system background and description, please see Kaplan and Hegarty's *Understanding GPS: Principles and Applications* (Kaplan & Hegarty, 2005).

3.1.2.1 – GPS Accuracy

The accuracy of the GPS unit is a major concern for our work. The original specifications for civilian-band GPS called for 13 m horizontal accuracy and 22 m horizontal accuracy at the 95% level when the system first came fully on-line with a 24-satellite constellation in 1995. Since then, the addition of further civilian signals allowing for dual frequency measurements as well as the disabling of the intentionally accuracy-degrading “selective availability” protocols by the United States government in 2000 have led to accuracies considerably better than the original specification (Kaplan & Hegarty, 2005). A Federal Aviation Administration (FAA) Performance Analysis Report examining data taken from 1 October to 31 December 2016 found that for 28 different test sites across North America, at the 95% level horizontal error was 1.89 m and vertical error was 3.87 m (William J. Hughes Technical Center WAAS T&E Team, 2017).

Unfortunately, there are also environmental factors that can further degrade performance. The National Coordination Office for Space-Based Positioning, Navigation, and Timing notes that inaccuracies can be introduced when GPS signals are blocked (for example, by “buildings, bridges, trees, etc.”), or when signals are reflected in multipath errors, as in figure 3.8 (National Coordination Office for Space-Based Positioning Navigation and Timing, 2017).

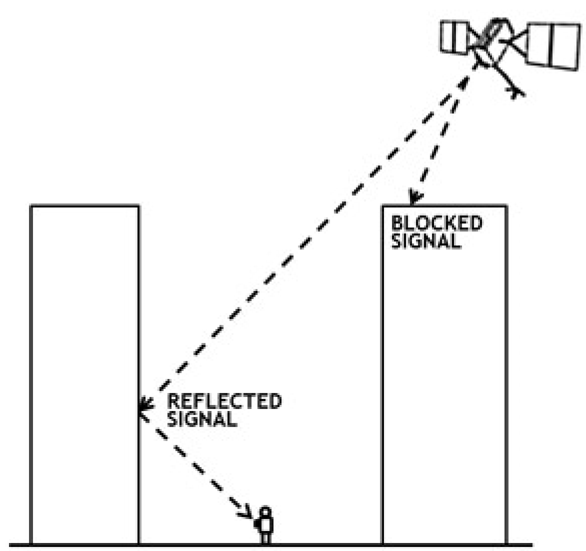

Figure 3.8: Multipath error causing misrepresentation of GPS user’s location, as in an “urban canyon” scenario (National Coordination Office for Space-Based Positioning Navigation and Timing, 2017).

These sorts of blockages and multipath errors are much more likely in densely built-up environments with many tall buildings around, sometimes termed “urban canyons.” Thus, placement of open lengths using GPS may be somewhat less accurate in these areas. At the same time, these densely built and populated areas are often those where good data on available street parking would be most useful. We generally term GPS inaccuracies “GPS drift.” Unfortunately, without taking multiple runs in the same place or having fixed, carefully measured reference points to compare to, there is little that can be done with the vehicle-integrated system to improve this accuracy.

3.1.2.2 – GPS Update Rate

The GPS unit in our lab vehicle has an update rate of 1 Hz. The ultrasound and speed telemetry, on the other hand, updates at 25 Hz. We interpolate in between the GPS points to match the 25 Hz frequencies of the other sensors to give latitude and longitude coordinates for the midpoint of each detected opening. When making a turn the result is only a straight-line approximation between the measured points, which can introduce slight inaccuracies. However, as the system is not trying to extrapolate to the next point but rather interpolating between known points, we are able to avoid most of the common issues stemming from changes in vehicle heading while extrapolating position. A faster GPS update frequency would help eliminate some of the interpolation uncertainty (for example, Mathur et al. specify a 5 Hz update frequency GPS unit) (Mathur et al., 2010). However, the manufacturer of our vehicle apparently considered 1 Hz appropriate for on-board navigation, and Kaplan and Hagerty agree that 1 Hz is sufficient for most GPS applications other than military aviation (Kaplan & Hegarty, 2005).

3.1.3 – Parking Spot Specifications

Understanding the sizes of parking spots is helpful in placing these accuracy measures in context. In general, perpendicular parking spots in the United States are about 3 m wide and 6 m long, though specific regulations can vary by state or city. For example, Washington, DC sets 9 ft wide and 19 ft long (2.7 m, 5.8 m) as the minimums for regular perpendicular parking spots and 8 ft wide and 16 ft long (2.4 m, 4.9 m) as the minimums for compact spots (Washington DC Office of the Secretary). In another part of the US, Texas has no length requirement but does specify that parking spot width must be at least 96 in (2.4 m) (Texas Department of Licensing and Registration, 2012). Other countries may have standards similar to or even smaller than compact spots in the United States; for example, code in France specifies perpendicular spots as being a minimum of only 2.3 m wide and 5 m long (Association Française de Normalisation, 1994).

Parallel parking space lengths are often not individually marked off and can thus be somewhat more variable. However, where spaces are marked, the Federal Highway Administration's (FWHA) "Manual on Uniform Traffic Control Devices" does specify that curbside parking spaces should be a minimum of 20 ft long (6.1 m) for spaces near intersections and 22 to 26 ft long (6.7 m to 7.9 m) for other spaces. Parking space width should be 8 ft (2.4 m) (Federal Highway Administration, 2012). Other work in this area has assumed a 6 m length for parallel spot length when dealing with unmarked areas (Mathur et al., 2010).

In terms of lanes of travel themselves, the FHWA specifies lane widths of 2.7 to 3.6 m, excluding ramps. Roadways with more daily traffic should generally have lanes toward the upper end of that range to reduce accidents. These widths specifically are not meant to include "shoulders, curbs, and on-street parking areas," (Federal Highway Administration, 2014).

We can consider these spot lengths with our known ultrasound sensor and GPS unit update rates and a number of passing speeds to determine how many data points we should see in any one spot while driving by at a given speed. Tables 3.1 and 3.2 present these numbers for a 2.7 m wide, 6.1 m long spot and speeds from 8 to 48.3 km/h (5 to 30 mph). Note that these give the number of data points for the spot as a whole; any parked vehicles will usually not take up the entire width or length of the spot and will be seen as fewer data points. For the same reason, open spaces will likely have a few more points than stated. In order to be confident of having a sufficient number of data points to make accurate measurements, data was only collected when the vehicle speed was 32.2 km/h (20 mph) or lower.

Table 3.1: Number of data points collected by 25 Hz update rate ultrasound sensors for various lengths and vehicle speeds.

Number of ultrasound data points collected		
	Length (m)	
Vehicle speed (km/h)	**2.7**	**6.1**
8	30	68
16.1	15	34
32.2	7	17
48.3	5	11

Table 3.2: Number of GPS points collected by 1 Hz update rate GPS unit for various lengths and vehicle speeds.

Number of GPS points collected		
	Length (m)	
Vehicle speed (km/h)	**2.7**	**6.1**
8	1.2	2.7
16.1	0.6	1.4
32.2	0.3	0.7
48.3	0.2	0.5

3.2 – Map Data Validation

Once ultrasound data has been collected and open lengths have been identified and located, the lengths must somehow be checked to ensure that they are open parking spaces before being used to inform drivers. There are numerous openings both on streets and in parking lots that are not valid parking. Shoulders on roads or freeways, intersections, bus stops, or fire lanes on roads with street parking, parking aisle intersections, handicapped parking spots, or shopping cart returns in parking lots may all appear as open to ultrasound sensors but in reality be impossible or illegal to park at.

As previously discussed, static parking occupancy detection systems do not have this issue. Single-spot detectors are only placed at valid spots. Mathur et al., who described vehicle detection with ultrasound sensors, state that "[w]e assume that maps of areas with street-parking slots are available from another source" and suggest that such maps may either be available from municipalities or built up over time from collected data (consistently closed lengths are probably not vehicles, and consistently open lengths are probably not valid parking; areas with consistent turnover of vehicle-sized objects are likely valid parking spots) (Mathur et al., 2010).

While these sorts of methods for parking-map construction will almost certainly be valuable in the future, they represent more piecemeal approaches that will likely take some time to come to fruition. Maps will have to be obtained from different towns and cities, standardized, and kept updated. Methods relying on historical data will take time to build up enough data to make conclusions and may be doubly sensitive to GPS drift issues (both on collection and on scanning for available parking against the historical map). However, in many areas, detailed road maps already exist in electronic form, created and maintained by organizations such as Google Maps, Microsoft's Bing Maps, or AOL's Mapquest. If these sorts of detailed maps contain the right type of information, they could be used to check the parking viability of detected openings. Additionally, they already cover most populated areas, are uniform in data format (at least within a single system), and are maintained by organizations with a strong interest in keeping the data as up-to-date as possible.

3.2.1 – Selection of Map Database

For this project, we chose to work with data from an open- and crowd-source map project called OpenStreetMap (OSM) instead one of the large corporate map services. In general, we found the information available to the public from OSM much more useful than what is available from other mapping projects' proprietary data. Of these, Google Maps at least is certainly interested in parking – the Google Maps app recently introduced a "parking availability" prediction feature, based on historical data (Albertson, 2017) – but they also tend to obscure any specific data they may have on parking-relevant features from users' views.

Compare figures 3.9 and 3.10: figure 3.9 is a screenshot of the results of a search for "parking" in Google Maps, on the campus of the Georgia Institute of Technology, just south of Fifth Street and west of I-75/I-85 in Atlanta, GA. Figure 3.10 is the same area in OSM. Google Maps marks a parking deck, and is even able to identify what type of university-issued parking pass is required to park there. OSM, on the other hand, marks the same parking deck, but also clearly shows surface parking lots in the area (in yellow). Furthermore, enabling more data layers in OSM and selecting one of the roads in the image, as in figure 3.11, reveals that the road itself has a "parking:lane:both = parallel" tag associated with it, indicating that parallel parking is available on both sides of the road there. That same level of detail is not available from Google

Maps, though many of those features are often visible when switching to the overhead images view.

OSM's more complete data and simple, standardized tag system made it the obvious choice to us over Google Maps when trying to find a database that would enable decision-making about possible parking spots. Bing Maps and Mapquest found no results whatsoever in this area and generally seemed much sparser in their parking-related data; they were only briefly considered. It is also possible that Google does have the sort of data that we need, but does not publicly display it in Google Maps (for example, Google Earth Pro offers more traffic pattern data than is available in Maps), but we were not able to find any such publicly available data from them.

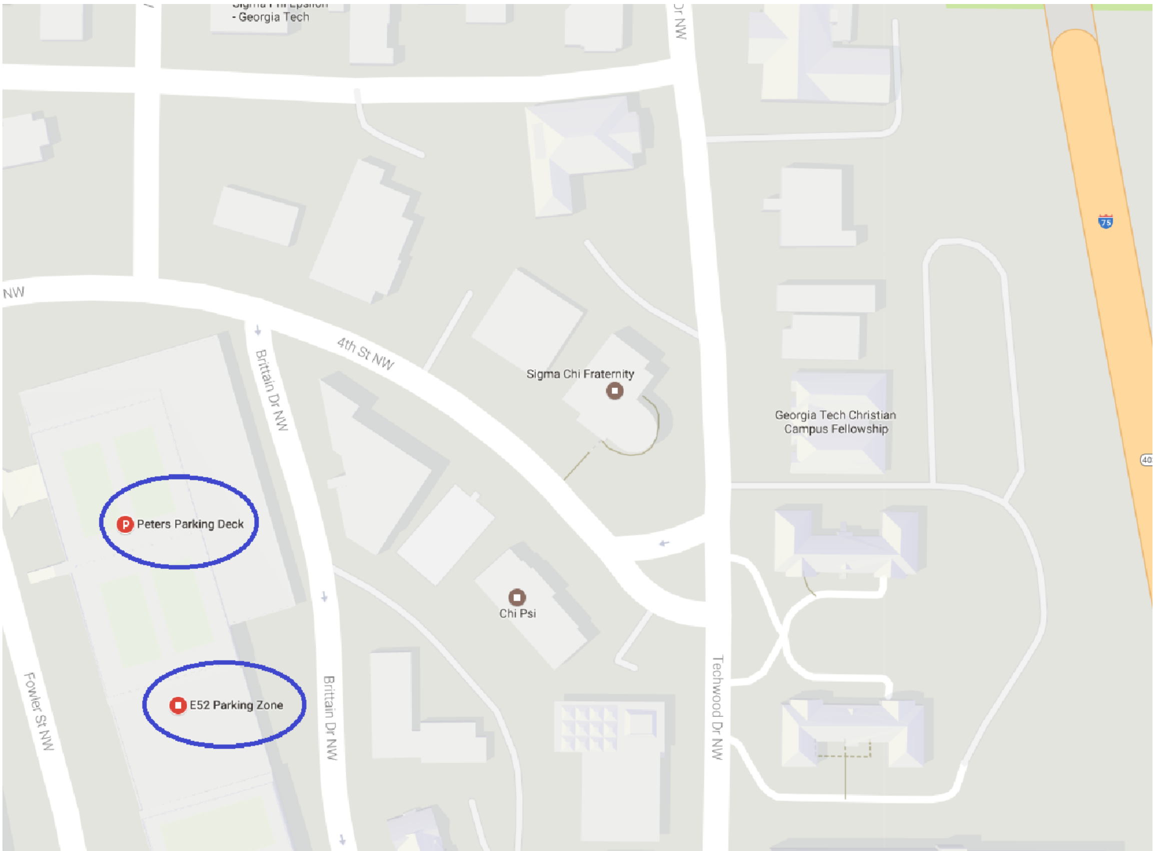

Figure 3.9: Google Maps search results for parking on a section of the Georgia Institute of Technology, circled in blue (Google Maps, 2017).

Figure 3.10: OpenStreetMap view of the same area as in figure 3.9, showing the same parking deck as well as lot parking areas (in yellow) (OpenStreetMap Contributors, 2017).

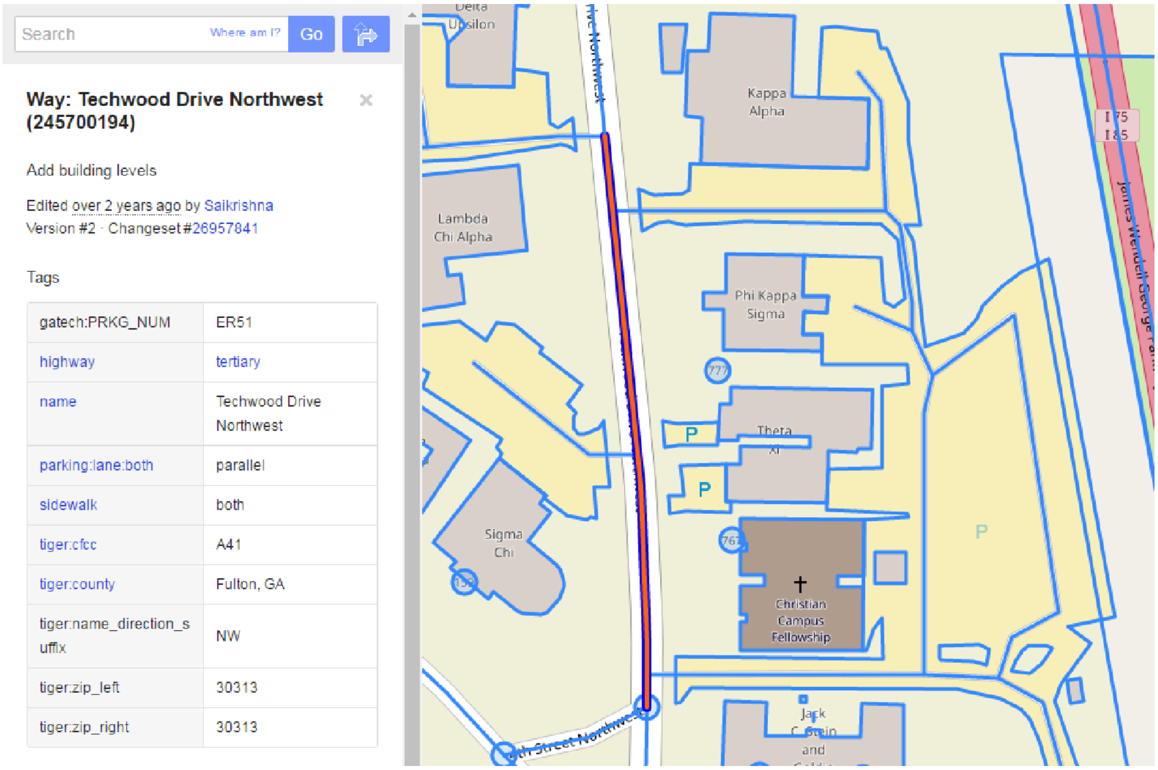

Figure 3.11: View in OpenStreetMap of a road segment with associated tags (OpenStreetMap Contributors, 2017).

3.2.2 – OpenStreetMap

OSM and other crowdsourced mapping projects are often referred to as being based on "Volunteered Geographical Information," (VGI). In the case of OSM, this can include GPS traces recorded by contributors as well as taking data from older maps that are now out of copyright ("Out-of-copyright maps," 2016), or making traces of aerial images – OSM used Yahoo! Maps aerial images from 2007-2011 and later switched to tracing from Bing Maps ("Yahoo! Aerial Imagery," 2016). OSM has also used public-domain data when available, such as the US Census's 2005 TIGER dataset which was imported in 2007-2008 to form the backbone of the US maps ("TIGER," 2017).

There is some question of accuracy when building a map largely dependent on VGI. A study comparing OSM data for the city of London to Ordnance Survey (the official mapping organization of Great Britain) data found that OSM data was on average within 6 m of the positions recorded by the Ordnance Survey (Haklay, 2010), while a 2012 study in Heidelberg, Germany found an average 5.2 m OSM error from survey data (Helbich, Amelunxen, Neis, & Zipf, 2012). Helbich et al. also point out that in some cases there may be a disconnect between topological accuracy and positional accuracy – a map may be correct in terms of which roads connect to which other roads but the location of the intersection may be off by several meters (Helbich et al., 2012). US accuracy measurements are somewhat less well-published (possibly because OSM started off as a European project, in London) but a limited study in 2013 intended as a proof-of-concept for an accuracy assessment technique found that for an area near Purdue University in West Lafayette, IL, OSM's root mean square positional error was 4.3 m (Canavosio-Zuzelski, Agouris, & Doucette, 2013).

3.2.2.1 – OpenStreetMap Data Organization

OpenStreetMap is based on three core elements: nodes, ways, and relations. Nodes are the simplest elements, containing a latitude value, a longitude value, and an ID (and sometimes elevation, though this is not required). Multiple nodes are combined to form ways, which can be either simple lines or the boundaries of areas. For example, the section of the street in figure 3.11 contains 8 different nodes, of which 5 are shared with other ways, which include intersecting driveways or roads, or other segments of the same road. Relations are somewhat more open-ended – OSM defines a relation as "multi-purpose data structure that documents a relationship between two or more data elements (nodes, ways, and/or other relations)" and states that they are dependent on their tags to give them meaning. The segment of road in figure 3.7 is part of two relations, both tagged as bus routes. Tags can be applied to any of the three core elements and give some sort of information about the element. They always contain both a key and a value; the list of tags in figure 3.11 has keys in the left column and values in the right. A few of the tags are very location-specific, such as the “gatech:PRKG_NUM = ER51” indicating the required Georgia Institute of Technology parking pass for that street, while others are very general, such as “highway = tertiary”, which is found on smaller roads everywhere ("Elements," 2017).

Our system deals mostly with nodes, ways, and their tags. Given a point defined with latitude and longitude, such as the openings detected by the ultrasound sensors and positioned with the vehicle’s GPS, we can check a small area around that point to see if any nodes or ways in the area have certain tags. This search is known is a “query.” If we know the appropriate tags to search for, we can determine if the point is in a valid parking area. For example, a query that returns a street parking tag is likely parking, unless it also returns a bus stop tag, in which case the opening is probably for the bus stop and not an available parking spot. With the appropriate tag searches and algorithms, it is thus possible to check individual GPS points against OSM to determine if the point is in a valid parking spot.

As an illustration, figure 3.12 is the result of one query using the online Overpass Turbo tool at http://overpass-turbo.eu/ developed by Martin Raifer (Raifer, 2017). The code on the left uses the Overpass API to look for bus stops, querying nodes, ways, and relations for the “public_transport = platform” tag. The search area is set to “bbox”, short for “bounding box, which in Overpass Turbo is the area visible in the map to the right. When the query is run, all nodes, ways, or relations containing the tag within the bounding box are returned, and results are displayed as the blue-edged yellow circles on the map.

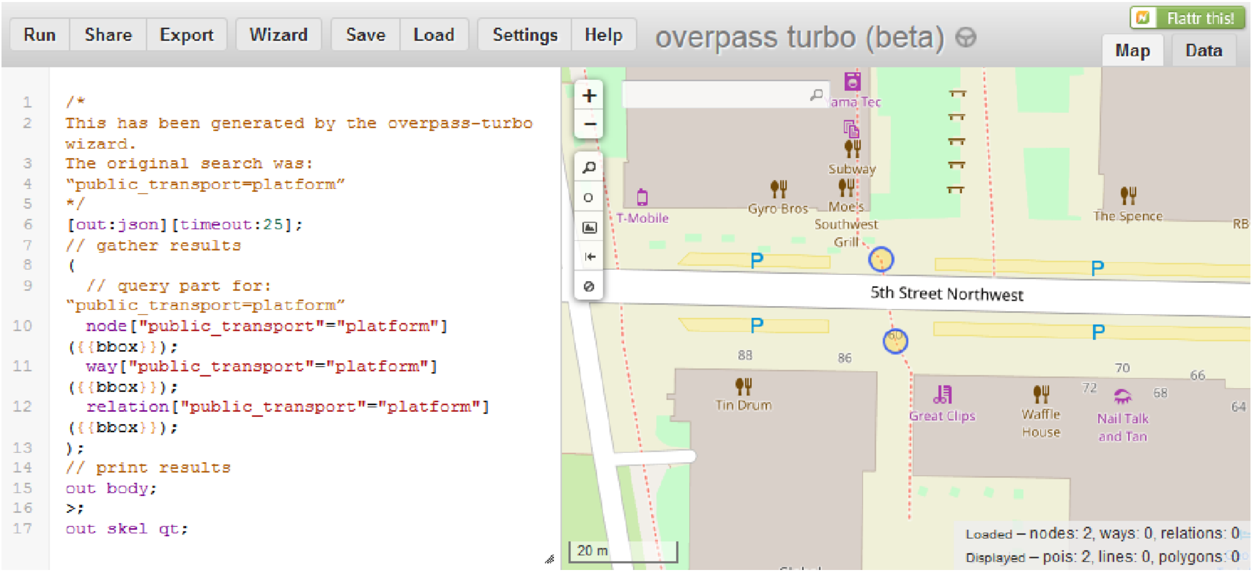

Figure 3.12: Example of a query for bus stops in OSM, illustrated using the Overpass API and Overpass Turbo online tool (Raifer, 2017).

Chapter 3 Summary

Our proposed mobile parking occupancy detection system relies on two main sources of information: data collected by the vehicle's own sensors, and map data from a source such as OpenStreetMap with information on parking lots and on-street parking. The vehicle's sensors can be further broken down into ultrasound and GPS systems. The park-assist ultrasound system is limited in range and precision when compared to lidar or radar systems, but ultrasound has the benefit of being less expensive and much more widely available on current production vehicles. Civilian GPS accuracy has steadily improved since its initial introduction, but drift may still be a concern. Current accuracy is 1.9 m horizontal at the 95% level; parking spots are usually roughly 2 m by 6 m. Finally, map data with good parking information may be able to determine whether an opening detected by ultrasound sensors is valid parking, without the need for a map of all individual parking spots in an area. We believe the crowdsourced OpenStreetMap project is the best option for this sort of map database at this time, with detailed information for street and lot parking and a well-defined and accessible organization method for its data.

CHAPTER 4

METHODS

In this chapter, we will discuss the methods and operation of the parking space occupancy detection system we developed using the technologies described in chapter 3. These methods are illustrated with preliminary results from both ultrasound data and OpenStreetMap datasets.

4.1 – Data Collection

Our data collection system was a 2016 Ford Fusion Energi, a late-model production sedan with integrated ultrasound parking assist technology and GPS receiver. Exact specifications for the ultrasound system were not available but experimentation suggested that they were in line with industry standards as described by Fleming in 2008: the sensors have generally a 0 to 4 m range, with occasional readings to 5 m, and update every 0.04 s, or at 25 Hz. An article by Day in 2006 describing one particular ultrasound parking assist system made by Valeo noted that the sensors had a 70 degree horizontal view; this concurs with our experimental observations of a roughly 60 degree view for our system (Day, 2006). As integrated parts of the vehicle, the parking assist sensors and GPS unit both publish their data as messages to the vehicle's CAN bus. We were able to collect the ultrasound data as well as other vehicle telemetry (speed, steering wheel angle) and GPS position and heading simultaneously from the CAN bus through the vehicle's OBD-II port, using Vector Informatik's CANalyzer tool.

Because the ultrasound sensors and vehicle telemetry are all published to the CAN bus as different messages, a small amount of processing of the raw data is necessary before analysis can begin. The ultrasound signals updating at 25 Hz are the primary interest, so the processing works to associate the most accurate value from the other sources to each ultrasound data point. Vehicle speed and steering wheel angle update at 50 Hz, twice as fast as the ultrasound sensors, and so each ultrasound point simply has the most recent speed and steering wheel angle assigned to it. As previously described, GPS updates at only 1 Hz. At 8.3 m/s (30 kph, 19 mph), one could drive entirely past a 6.4 m-long half-ton pickup truck without having a single GPS point associated with the truck's actual location. For this reason, GPS points are interpolated between recorded values to give finer data to associate with each ultrasound data point.

Once this processing has taken place, each ultrasound value has a timestamp and a vehicle speed associated with it. We then calculate the difference in time (the ultrasound messages do not publish to the CAN bus exactly every 0.04 s, so this is calculated and not assumed) and average vehicle speed between each two consecutive ultrasound data points. Since we know that the distances measured by ultrasound are perpendicular to the direction the vehicle is traveling, it is then possible to calculate distance traveled between the consecutive points. This allows us to move from the one-dimensional ultrasound data to a two-dimensional distance traveled vs. ultrasound measured distance plot, as in figures 4.1 and 4.2. Figure 4.1 shows several cars parked in 90 degree, or perpendicular, parking spaces; figure 4.2 shows cars parked in 0 degree, or parallel, parking spaces. Compare the slightly curved returns from the bumpers in figure 4.1 to the relatively straight sides of vehicles in figure 4.2. If the sensors do not receive any echo, such as for open spaces with no surface to reflect from, a 0 m measurement is returned.

Figure 4.1: Ultrasound signals returned for a row of perpendicular-parked cars.

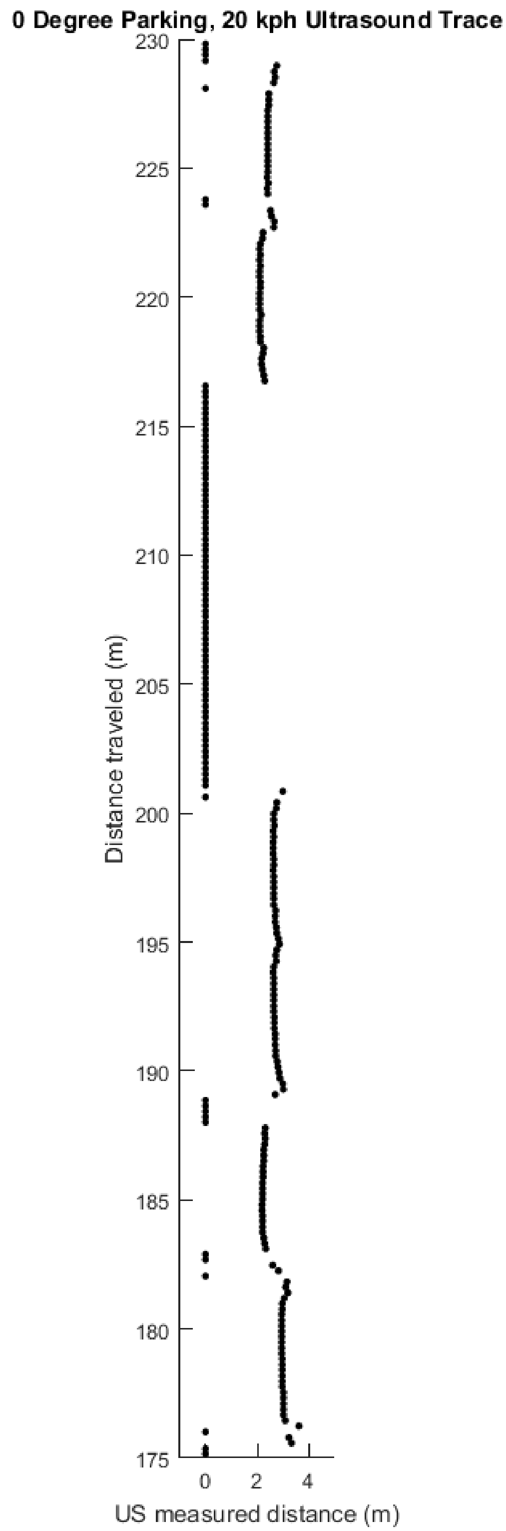

Figure 4.2: Ultrasound signals returned for a row of parallel-parked cars.

This combined vehicle-speed and GPS system does vary from some previous approaches by other groups. Mathur et al. state that "the errors in location estimates obtained from a GPS receiver can distort the true length of the car in a somewhat random manner," and they use multiple data collection runs to manually designate fixed reference objects for GPS error correction by "environmental fingerprinting," (Mathur et al., 2010). We find the time-vehicle speed method to be simple and accurate for open spot detection with a single run, and prefer it to GPS-based measurements in order to better preserve the true length of the detected objects.

4.2 – Available Spot Detection

Figures 4.1 and 4.2 suggest a simple approach for finding open parking spaces: search for continuous lengths of 0 values, above whatever the minimum parking spot length or width should be. This is in fact how our spot detection method works, but width distortion effects must be kept in mind when determining the minimum threshold length that may be marked as a possible open parking spot.

As described in section 3.1.1.1, data taken with cone-shaped ultrasound beams are susceptible to some amount of width distortion that makes openings between two parked vehicles appear smaller than they really are. Thus, a 3 m opening between two perpendicular parked cars may only appear in the ultrasound data as a 1.6 m opening, with the effect worsening as the sensing car drives past the parked cars at a greater distance or a higher speed. As an example, width distortion is particularly evident in figure 4.2 from 190 to 200 m, where the two parallel-parked cars shown in figure 4.3 are blended together into a single continuous signal. Because of this distortion, we considered a 1 m opening to be the minimum for perpendicular parking and 4 m for parallel parking. For comparison, recall from section 3.1.3 that parking spaces in the United States are usually around 2.7 m wide and 6.1 m long. These threshold values were also influenced by the initial controlled testing described in section 5.1.

Once the open lengths are identified, the GPS point (likely interpolated) for the vehicle's position when the middle ultrasound value in the opening was recorded is used to extrapolate the location of the opening itself. Direction is given by shifting vehicle heading 90 degrees clockwise (for the right-side sensors). Distance from the vehicle to the opening is calculated as the average of the distance to bumpers of the previous and following detected vehicles, plus 2 m. This allows us to work with the location of the opening itself, rather than the location of the sensing vehicle when it detected the opening.

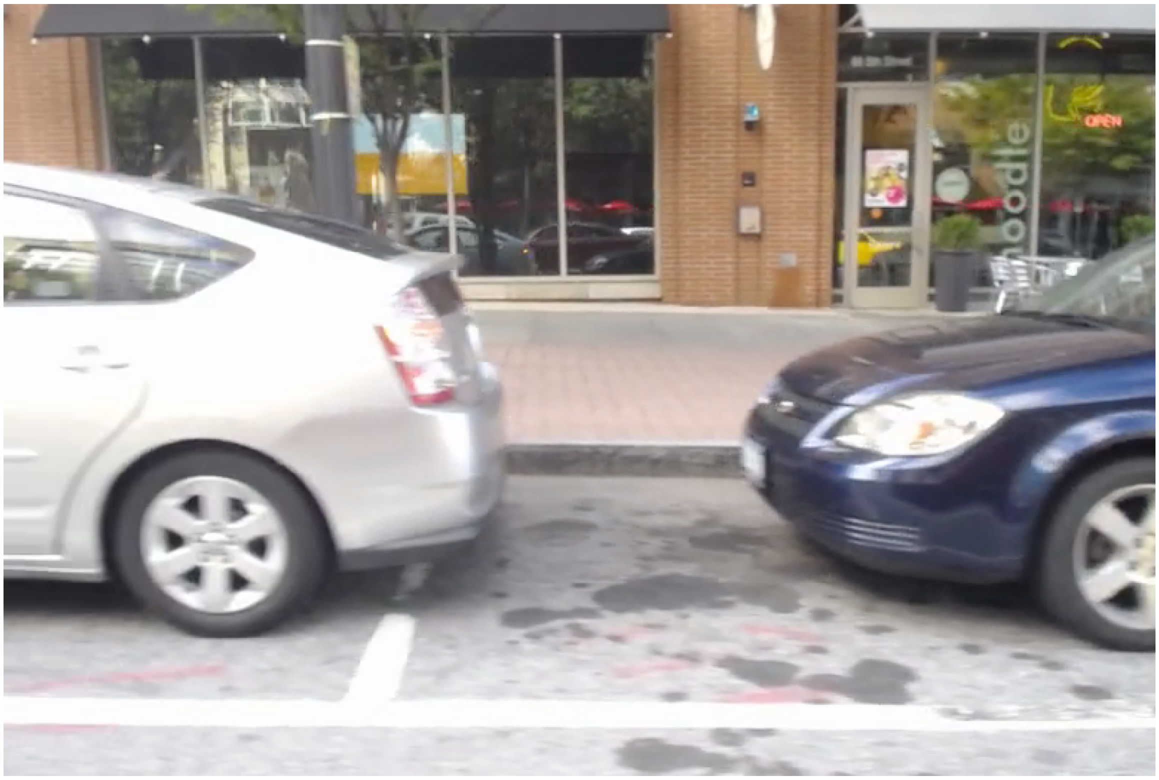

Figure 4.3: Open space between two parallel parked cars corresponding to the 195 m mark in figure 4.2.

4.2.1 – Vehicle Detection

Previous work has devoted considerable time and attention to marking and counting parked cars. For our system, we found this to be generally more plausible for cars in parallel parking configurations than for cars in lot parking. Detection of objects such as vehicles is often complicated by noise issues, especially at the edge of vehicles. A good example of this is at 182 m in figure 4.2, where several 0 m values are interspersed with values from a vehicle’s bumper. The culprit is the particularly rounded rear corner of the black vehicle seen in figure 4.4 (a Honda Accord Coupe), which scatters enough of the ultrasound signal that no echo returns to the transducer.

Figure 4.4: The rounded rear corner bumper causing the noisy transition between two vehicles seen at 182 m in figure 4.2.

These sorts of noise issues are most common around the edges of vehicles but the ultrasound system is also more sensitive to non-planar surfaces when driving by at higher speeds or distances. For example, particularly irregular bumpers can occasionally return a handful of 0 m values in perpendicular parking situations. The return in figure 4.5 with one interrupting 0 m value was caused by the combination push bar/skid plate on the F150 in figure 4.6. The ultrasound sensors are able to detect the central protrusion, but the continuous return is broken up when one of the signals was sufficiently scattered to return a 0 m value.

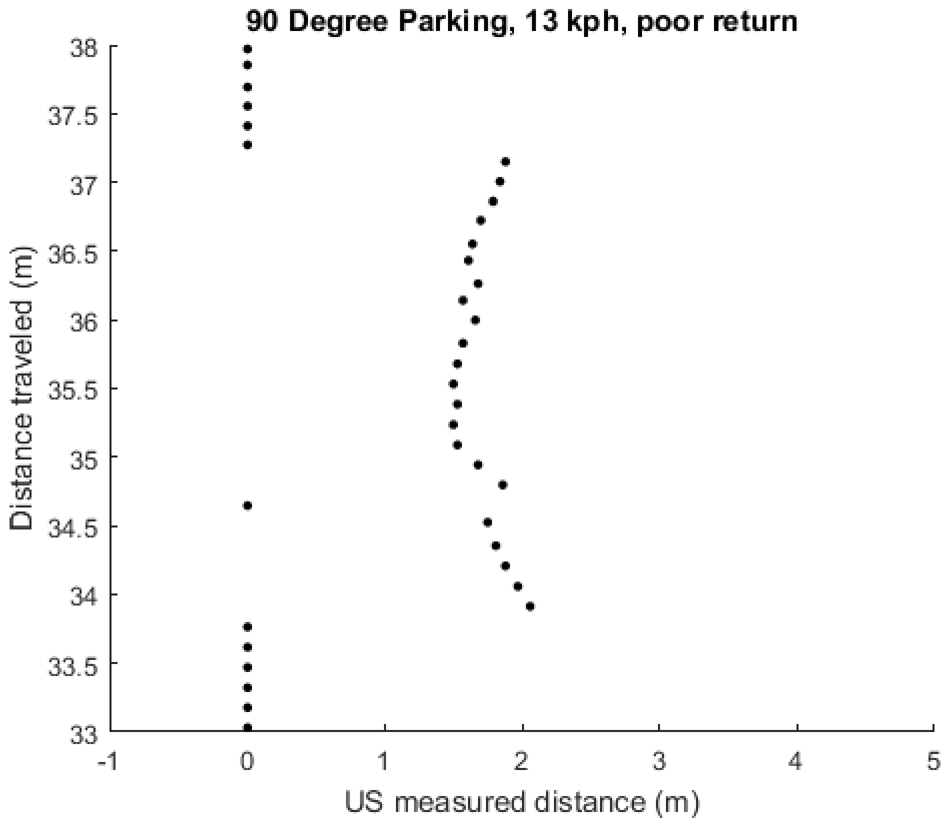

Figure 4.5: Ultrasound signal of a vehicle with an irregular bumper parked at 90 degrees, showing breakup of signal at one point.

Figure 4.6: Irregular bumper corresponding to ultrasound trace in figure 4.5.

Parking lots with non-perpendicular or parallel parking (i.e., cars parked at a 60 or 45 degree angle to the parking aisle) are particularly susceptible to this sort of noise, as seen in figure 4.7.

A handful of other groups have proposed or implemented solutions to this issue in efforts to count parked cars. Park et al.'s multi-echo "radial resolution" method for plane and corner detection might help with corner noise (Park et al., 2008), while Mathur et al. trained a system to determine appropriate threshold values for continuous signals to mark parked cars (though the system only had to deal with parallel parked vehicles) (Mathur et al., 2010). Our approach is simpler: only look for open spots.

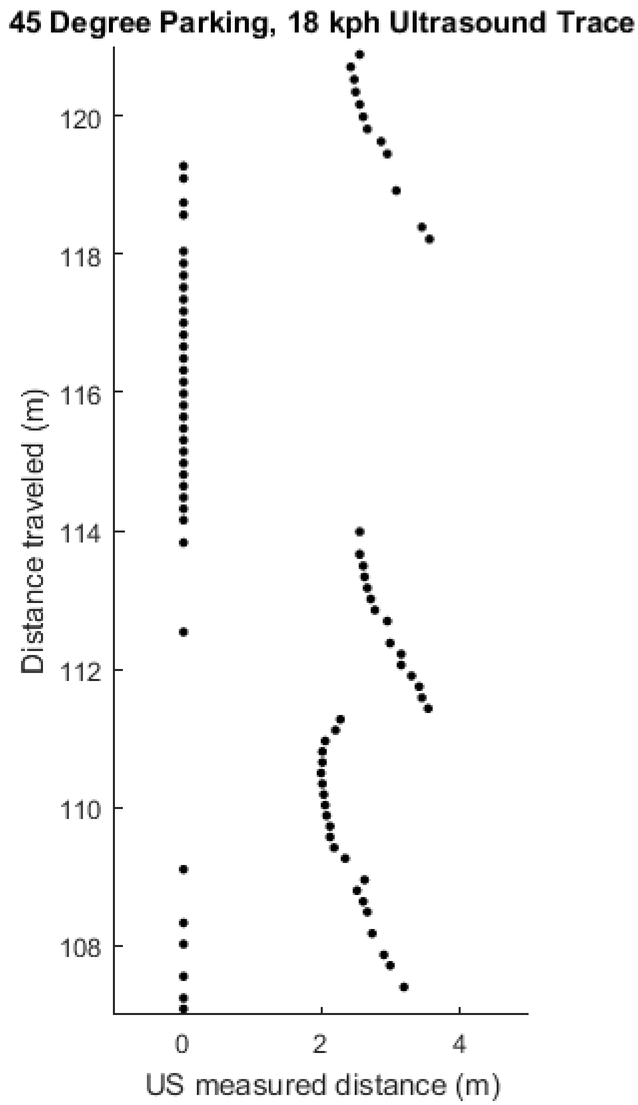

Figure 4.7: Relatively noisy ultrasound returns from cars parked at a 45-degree angle.

4.3 – Situational Awareness

Every opening seen by the ultrasound sensors will certainly not be a valid parking space. Others, such as Mathur et al., have suggested that this problem be solved by use of dedicated maps with the location of all parking spaces in a city marked on them (Mathur et al., 2010). We propose an alternate method: use currently existing map databases to make determinations regarding whether detected openings are in valid parking areas or not. We broadly term this process "situational awareness."

As described in section 3.2, OpenStreetMap seems to be the best choice in terms of both data quality and accessibility for this application. In our implementation, we set up a local OSM3S server containing the OSM data for the geographical region we were interested in (the state of Georgia, provided in useful form by Geofabrik GmbH, a free geodata processing service) (OpenStreetMap Contributors and Geofabrik GmbH, 2016), and queried it for our situational awareness using the Overpass API. There are publicly available instances of this API available online (the main one is at http://overpass-api.de/api, while http://overpass-turbo.eu will also return query results on a map), but these have two major weaknesses from our perspective: both take considerably more time to execute queries than a local database, and both have a limit to the number of daily requests that can be submitted. When trying to check a large number of potential parking spots using multiple OSM tag queries, it becomes rapidly apparent that a local instantiation is the sensible alternative. However, figure 3.12 remains a useful illustration of how our queries are built and function; we simply use much smaller search areas (bounding boxes) centered on the detected opening's location.

These following sections will describe both the situational awareness algorithm and the specific implementation and challenges in OSM.

4.3.1 – Cases Requiring Situational Awareness

Regardless of the map data used, the first goal must be to develop a list of cases that the algorithm should be able to deal with. In general, we assume that it is possible to tell if one is in a generally valid parking area, such as on a street with street parking or in a parking lot (each of these can be checked with a single query in OSM). The question to be answered then shifts to finding the exceptions: “where can you not park on a street with street parking” or “where can you not park in a parking lot.” Table 4.1 has a list of these exceptions for each domain. The algorithm at its most basic then functions by answering the questions “is this opening in a general parking area” and “is this opening in an exception to a parking area.”

For street parking, intersections are the single largest and most consistent exception; in addition to the opening created by the intersection itself the Federal Highway Administration in the US specifies a 20 ft (6.1 m) no-parking zone before any crosswalks (Federal Highway Administration, 2012). In busy areas with bus or tram service, openings needed for these public transportation systems must also be avoided. Finally, certain fire safety devices such as fire hydrants and fire lanes are illegal to obstruct.

Parking lots are in some ways more complicated, because they are generally defined as an area rather than a street’s essentially one-dimensional line or curve. Parking aisle intersections, handicap spots, storefronts or loading areas directly next to buildings, and shopping cart returns are all potential openings seen by ultrasound sensors within an area marked as a parking lot on a map. If a parking lot is very near a road and separated by a small distance, such as a sidewalk, openings in the road may also appear to be in the parking lot and should also be filtered.

Table 4.1: Exception cases for invalid parking within street parking and lot parking areas and relevant OpenStreetMap tags for situational awareness queries.

Parking Category	Exception Case	Relevant OSM Tags	Radius of search area
Street Parking	Intersections	highway = traffic_signals highway = stop At least 3 of any combination of: highway = footway highway = residential highway = unclassified highway = tertiary highway = secondary	10.7 m
	Public transportation stops	public_transport = platform public_transport = stop_position public_transport = stop_area public_transport = station	10.7 m
	Fire lanes, fire hydrants, fire zones	emergency = fire_hydrant parking:lane:(*side*) = fire_lane	6.1 m
Lot Parking	Parking aisle intersections	At least 2 of any combination of: service = parking_aisle highway = service	9.1 m
	Handicap spots	wheelchair = yes (lot specific, not spot specific, and not used)	N/A
	Storefronts, loading zones	building = yes	6.1 m
	Shopping cart returns	(none)	N/A
	In-road openings near parking lots	highway = residential highway = unclassified highway = tertiary highway = secondary	6.1 m

Once the required exception cases are understood, they must be translated into the language of whatever map data has been chosen. In our work, this means developing a query (tag search) for each of these cases within OpenStreetMap, as well as queries for the general parking areas. Depending on the map data used, some of these cases can be defined very simply, while others may be more complex. For example, OSM is generally good about explicitly defining bus stops, but intersections are often only sporadically tagged, so a simple algorithm must be developed to check the number of roads in an area to catch all intersection cases. Unless one is working with near-perfect map data with all exception causes already explicitly defined, this sort of adjustment will likely be necessary. In the worst case, the map may not even have enough data to make the roundabout query as for intersections; for example, OSM has a tag for the presence of handicap parking spots in parking lots but does not describe at all where in the lot these spaces are, leaving us effectively no way to flag handicap parking spots within the situational awareness algorithm.

OSM does consistently use several well-defined tags to indicate the general presence of parking. “amenity = parking” covers most garages and parking lots and “parking:lane:(side) = (type)” covers most street parking, with “side” indicating the side of the road and “type” being parallel, diagonal, or other applicable designations. If there is no parking tag found within the search area around our open length, we can be relatively certain that the spot is not in a valid parking area. If the query does return any of these tags, the exception queries must come into play to see if the opening should truly be considered legal parking. Additionally, if the parking tag returned uses a “parking:lane” key, then we know that openings are very likely in parallel configurations and choose a 4 m opening threshold, while for “amenity = parking” we know perpendicular or angled parking is more likely and choose a 1 m opening threshold. Finally, the queries can be executed with different search areas. We generally default to 6.1 m (25 ft) for the radius, but in several cases experimental results encouraged an increase to 9.1 m (30 ft) or 10.7 m (35 ft) in order to avoid false positives.

The remainder of this section will focus on how these queries can be executed within OSM.

4.3.2 – Street Parking in OSM

As described in table 4.1, street parking exceptions are mostly concerned with public transportation stops, fire hydrants and other safety exclusions, and intersections. Public transportation and fire safety are relatively straightforward to check for, while intersections can be somewhat more complicated.

For public transportation, the main concerns on roads are buses and trams (on-road light rail systems). OSM has a variety of values associated with the “public_transport” key; the most important of these are “platform” and “stop_position” for individual passenger waiting points and vehicle stop points respectively (often coincident), and “stop_area”, a relation tag used for multi-element public transport complexes. Also included is “station”, an area tag outlining a travel station’s area and usually included in a “stop_area” relation. Figure 4.8 shows an example of a node tagged as a bus stop outside the baseball stadium on the campus of the Georgia Institute of Technology.

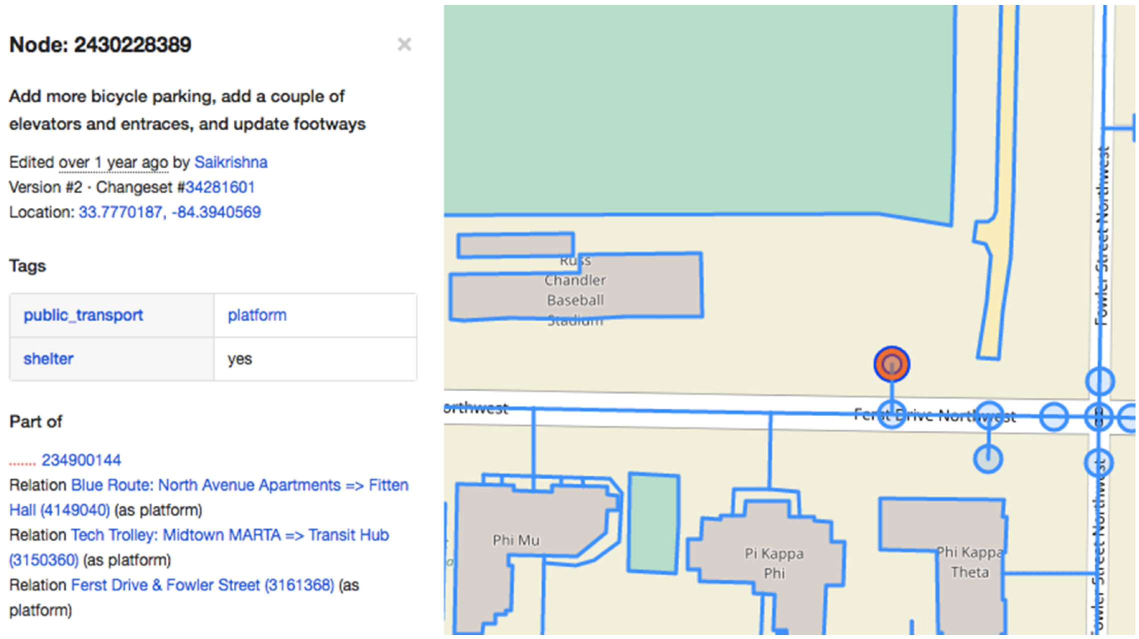

Figure 4.8: Bus stop node with "public_transport = platform" tag (OpenStreetMap Contributors, 2017).

Fire safety devices are handled similarly, though the tags are spread out over more keys than in public transportation. The "fire_lane" value can work with any of the "parking:lane:(side)" keys, while the "emergency = fire_hydrant" marks individual fire hydrants. Unfortunately, fire hydrants tend to be rather sporadically marked, especially in the US. In all of Atlanta and surrounding areas, there are only a handful of fire hydrants marked in the Virginia Highland neighborhood, with a few more in Decatur, GA. Fire safety devices in other larger cities are often only slightly better documented. For example, figure 4.9 shows a search of all fire hydrants in the Washington, DC area using the Overpass-Turbo tool; Washington, DC itself appears very sparsely marked while across the river the Arlington, VA neighborhoods of Pentagon City and to a lesser degree Virginia Square have a large number of tags. OSM data is often somewhat more comprehensive in Europe, but an examination of large cities there reveals similar patterns. Taking Berlin as another example, hydrants seem to be marked in a cluster roughly around the Str. des 17 Juni extending west from the old city center to Charlottenburg but are rarely marked in such number elsewhere in the city. As a result, the filter for fire safety devices may not catch some fire hydrants until map data improves and should be treated with some caution.

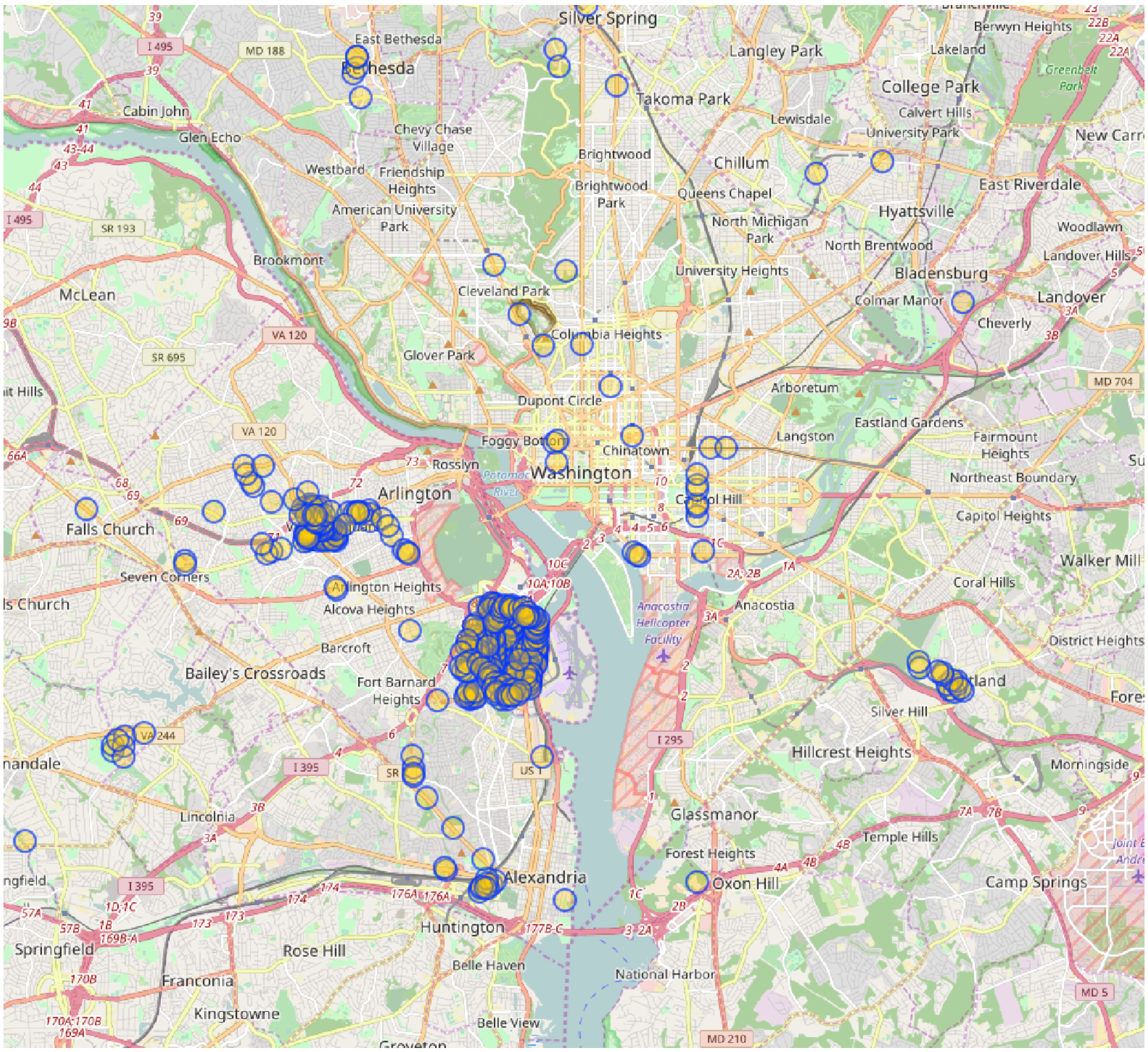

Figure 4.9: Fire hydrants marked in OSM in and around Washington, DC (from Overpass Turbo, Raifer 2017).

The query to determine if an opening is in an intersection is somewhat more complicated. Ideally, intersections will have a “highway = traffic_signals” where signal lights are present and a “highway = stop” tag where stop signs are present (for all-way stops; 2-way stops will technically be marked with the same tag at the end of the stopping roads but not actually at the intersection point). In practice, many intersections lack either one of these tags. Figure 4.10 is a result of searching both tags in Washington, DC, and at least in the downtown area, it looks like most intersections might actually be labeled correctly, though coverage seems to drop farther out. Figure 4.11 shows the same search in midtown Atlanta, GA near the campus of the Georgia Institute of Technology, where it is clear that the marking is nowhere near complete. Instead of being able to search for a handful of tags, we defined a list of possible roadway types (different values for the “highway” key) and determined that any time there were at least 3 different highway tags in an area, that area was likely an intersection. Because OSM sometimes breaks longer roads into multiple ways between intersections, a 2-tag threshold would occasionally report intersections where there are none. Combined, the traffic signals and stop sign tags and the multi-road tags enable us to detect most intersections and filter any openings in them from the list of valid parking spots.

Once these three filters are in place, the fourth remaining task is to check that the area actually is valid street parking. This is done by searching for the “parking:lane:(side) = parallel” tag with sides “left”, “right”, and “both” (“left” and “right” in OSM are in relation to the ways that make up roads, which are directional). Taken altogether, if nothing is returned for the public transportation, fire device, or intersection queries, while there is a return for the general street parking query, the detected opening is considered to be a valid street parking spot.

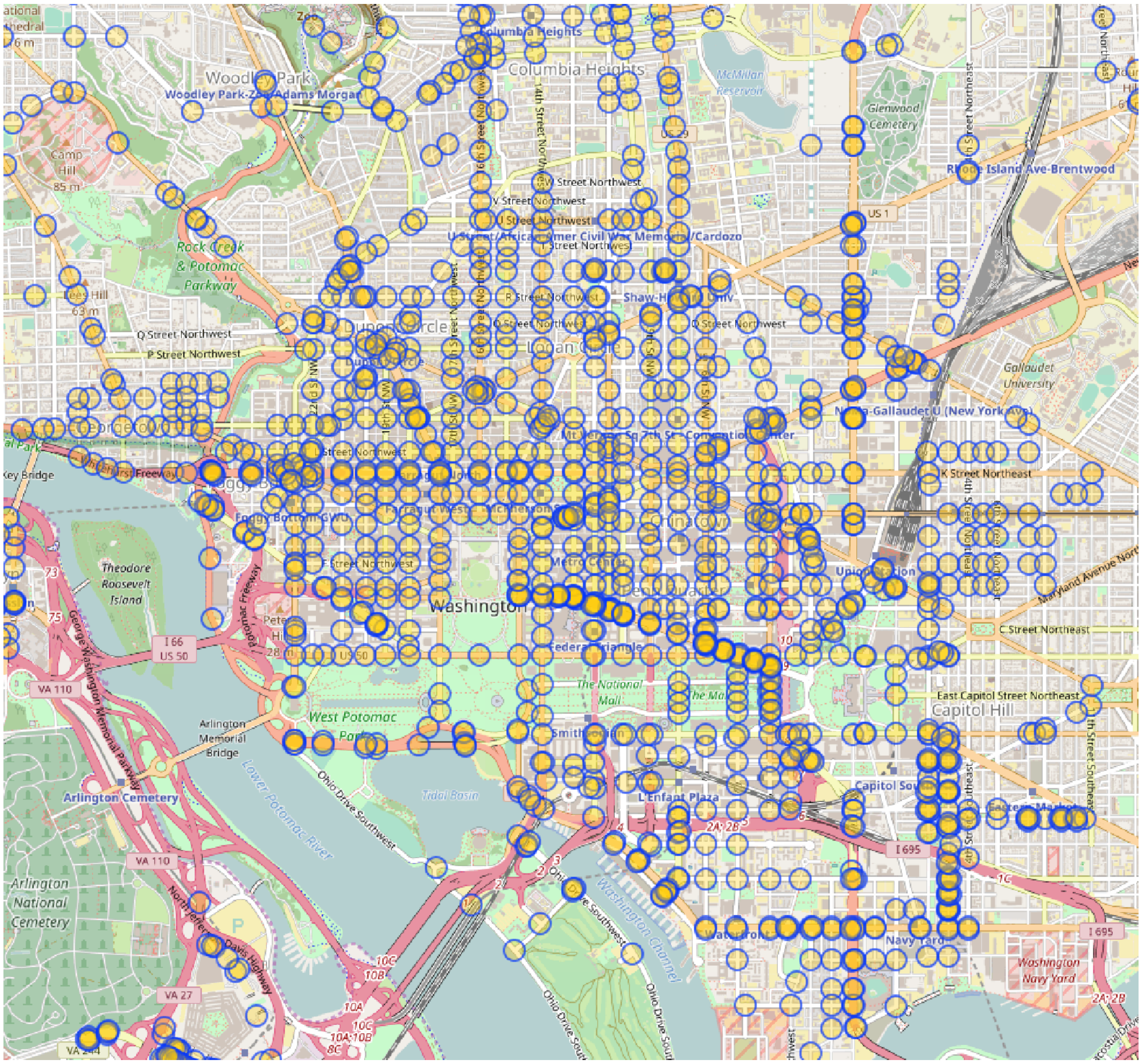

Figure 4.10: Marked street intersections in downtown Washington, DC with either “highway = traffic_signals” or “highway = stop” tags (from Overpass Turbo, Raifer 2017).

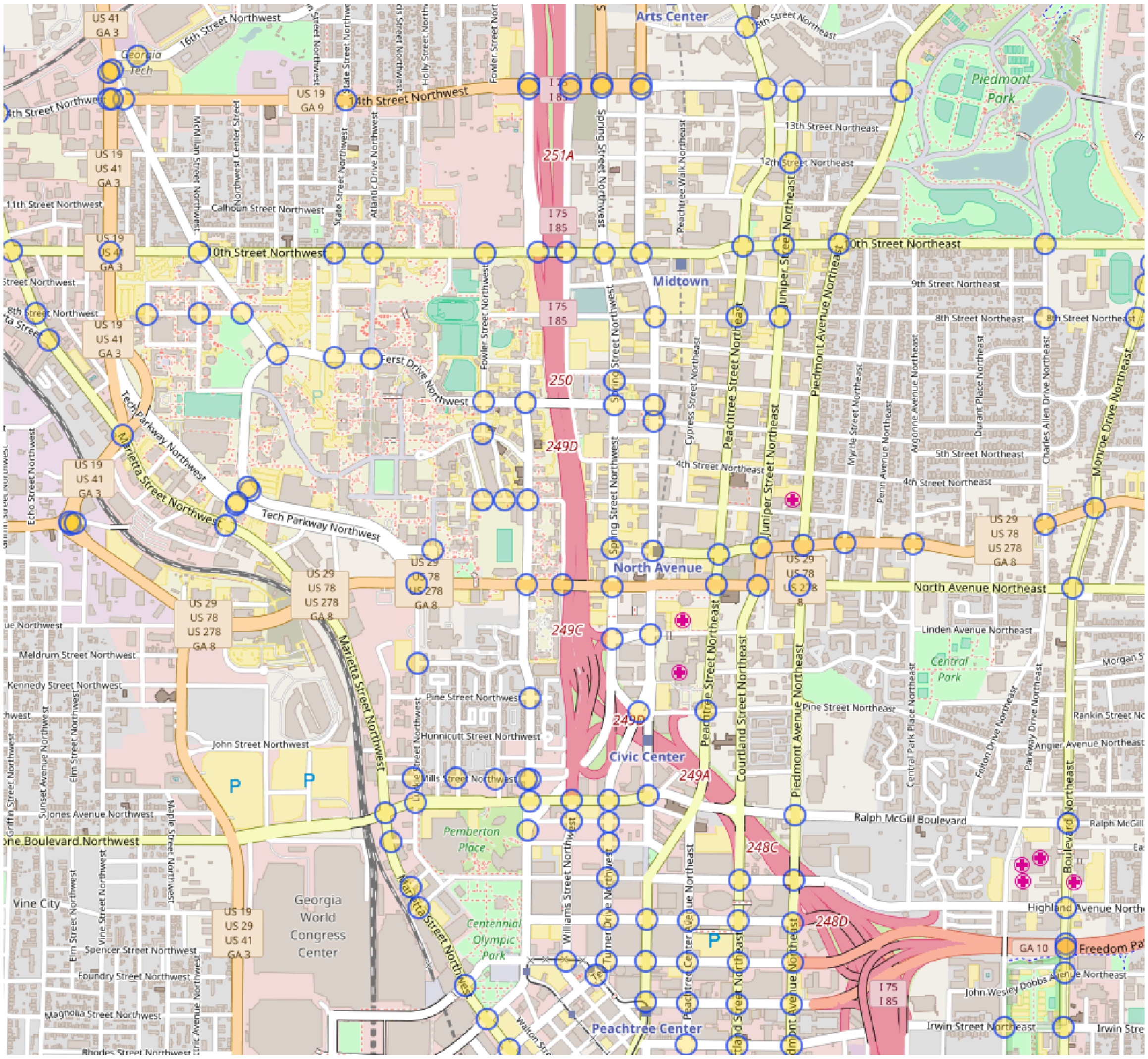

Figure 4.11: Marked street intersections in Atlanta, GA, near the campus of the Georgia Institute of Technology with either “highway = traffic_signals” or “highway = stop” tags (from Overpass Turbo, Raifer 2017).

4.3.3 – Lot Parking in OSM

Our situational awareness algorithm has also been designed to work within parking lots using a similar set of queries. Generally, the “amenity = parking” tag is used to indicate the areas of parking lots as in figure 4.12, but when searching for relevant tags around a GPS point, if the boundary of the area is not within the search radius, the area’s tag will not be returned.

Fortunately, larger parking lots often have parking aisles defined within them, with the "service = parking_aisle" tag, as seen in figure 4.13. As a result, we simply search for both tags when checking for the presence of parking lots.

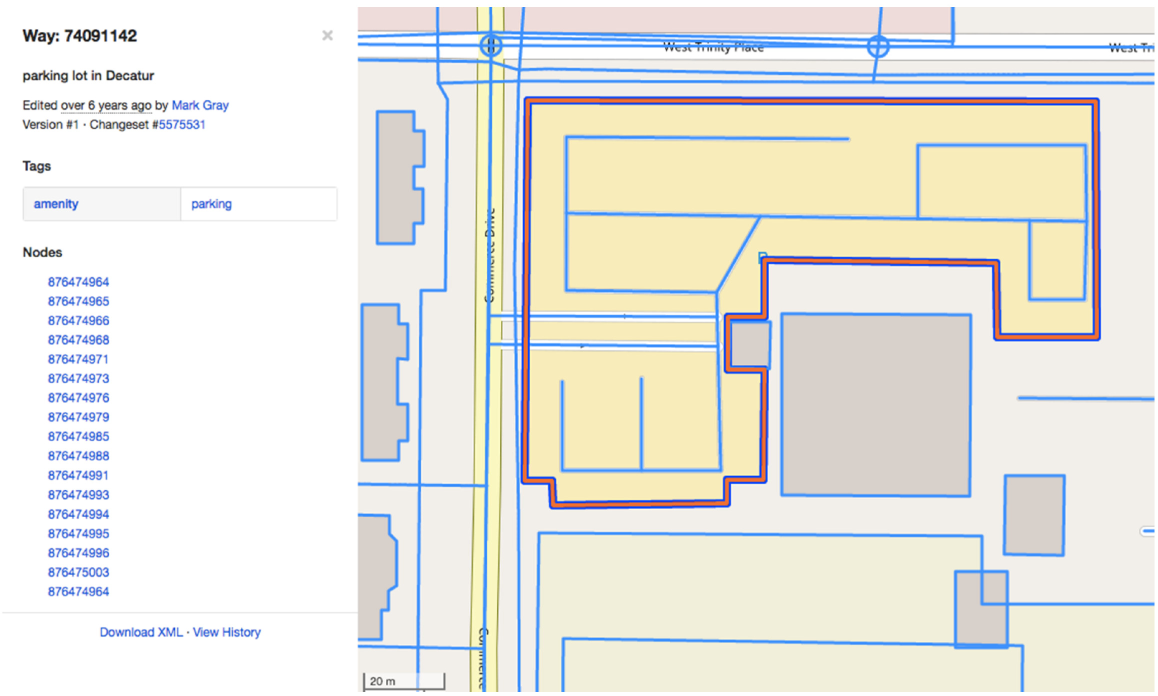

Figure 4.12: Parking lot boundary way, marked with "amenity = parking" tag (OpenStreetMap Contributors, 2017).

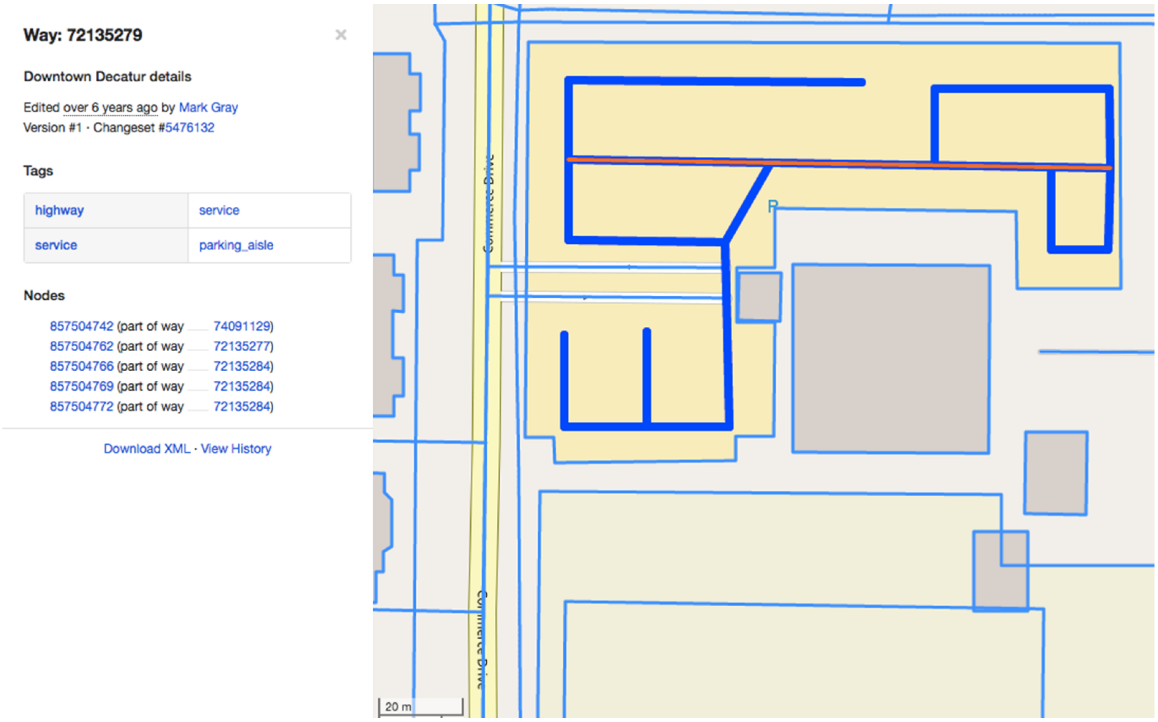

Figure 4.13: Parking aisles within a parking lot marked with “service = parking_aisle” tag (OpenStreetMap Contributors, 2017).

Intersections between parking aisles and other small roads around parking lots are handled similarly to the road intersection case, checking for multiple ways with the appropriate tag in the search area. The “highway = service” tag, seen in figure 4.17, is used to denote small roads of the sort found around parking areas even if they do not have parking spots lining them. Any two of “highway = service” or “service = parking_aisle” within the search radius will return an aisle intersection classification for the opening.

Open areas in front of stores are filtered by looking for the basic OSM building tag, “building = yes”, with a smaller search radius than is used for intersections, small enough so that it does not also filter out street parking in densely built urban areas. This may also be problematic for strip mall-style parking lots, where there are parking spots immediately in front of stores, though in our experience this parking configuration is less common in denser areas where a parking guidance system would be of most use.

Of the items listed in for parking lots in table 4.1, handicapped spots and shopping cart returns are not marked in any way in OSM. There is a “wheelchair” key to denote wheelchair accessible areas, but the spots are not marked within parking lots. Handicapped spots will always be at the front of lots, but their exact number and placement is too variable to be able to set up a single definitive algorithm to extrapolate their placement from OSM data. Another data source will be necessary to effectively filter the openings produced by handicapped spots. On the other hand, experimental data revealed that the racks in shopping cart returns almost always return enough of a signal that the initial algorithm does not consider them to be open lengths in the first place, removing the need to try and filter them.

Finally, as in figure 4.13, parking lots may be only a few meters separated from roads in some areas. Before marking any opening as being valid parking in a parking lot, a query with a very small search radius searches for a list of road tags (“highway = secondary”, “highway = tertiary”, etc.) to ensure that the opening is not in the road itself.

4.3.4 – Situational Awareness Decision-Making

These different queries are all executed for each open length to form a list of relevant tags associated with that length. Ultimately, users of this data will only see available parking spots, or possibly measures of likelihood of parking on certain streets or in certain areas. The general decision-making process for selecting the valid parking openings is detailed in figure 4.14. There are four possible outcomes for a detected opening shown.

Once the list of tags has been generated, the algorithm first checks for invalid street parking tags. If any are found, the opening is marked invalid. If there are no invalid tags but valid street parking tags are present, the opening threshold is increased to 4 m (from the default 1 m). Any openings below 4 m are discarded as being of insufficient length for a parking spot, and remaining openings are marked as valid parking and returned to the parking guidance information system. If no valid or invalid street parking tags are found, then the algorithm proceeds to checking lot-relevant tags. If invalid tags or tag combinations (aisle intersections) are found, the opening is marked invalid. If no invalid tags are present while valid parking area tags are found, the opening is marked valid parking with no need for threshold adjustment. Finally, an unknown classification occurs when the query returns no parking-relevant tags at all. Because queries do take time to run, we do not check for all known non-parking areas (e.g., the "highway = motorway" tag for major highways and interstates).

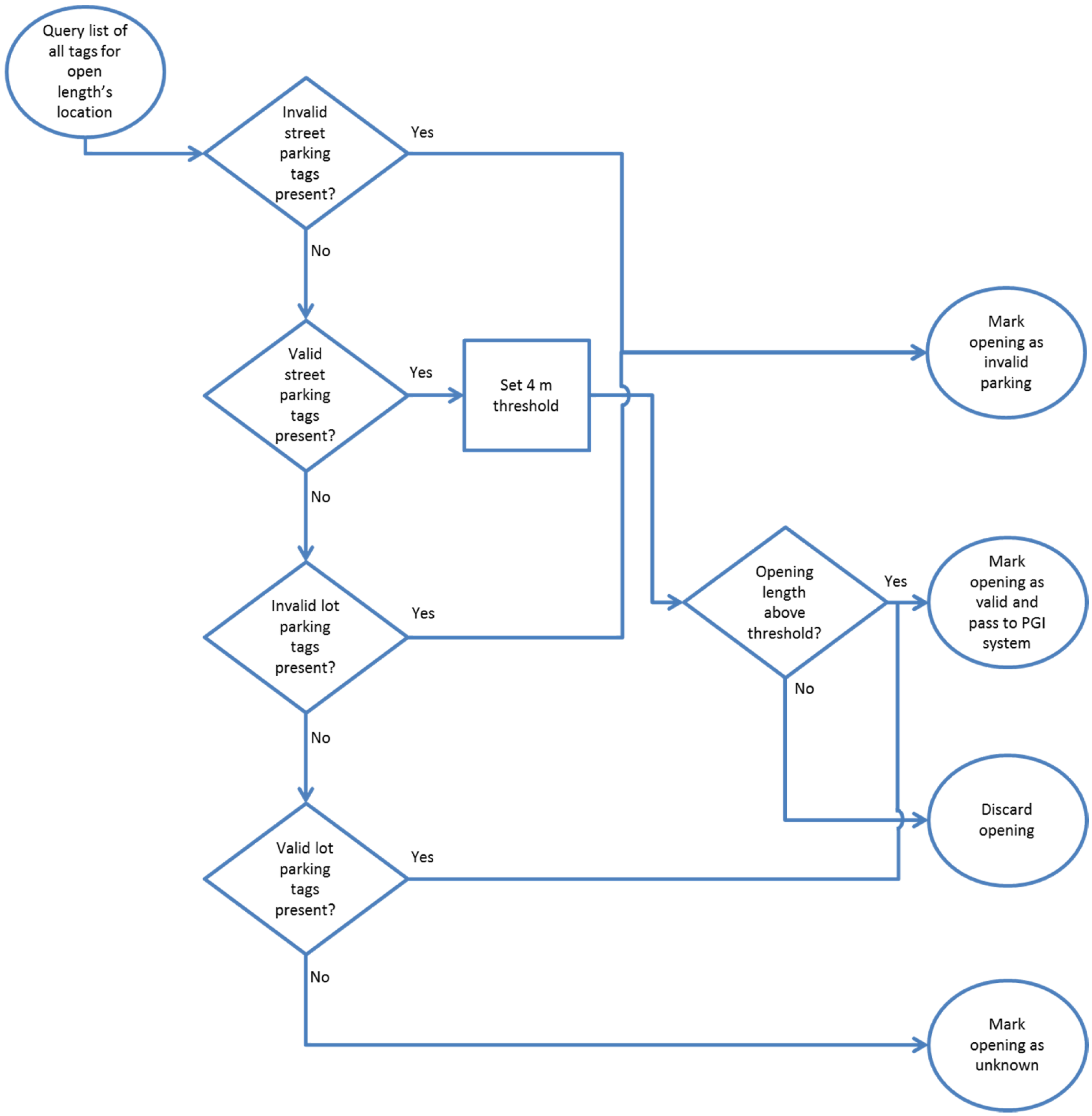

Figure 4.14: Flowchart for deciding whether an open length should be considered valid parking based on data from OSM.

Chapter 4 Summary

Data collection is to be performed with a late-model sedan equipped from the manufacturer with both ultrasound parking assist sensors and a GPS unit, both of which can be read from the CAN bus. The ultrasound data can be combined with time and speed data to make a distance traveled vs. ultrasound plot, showing what the ultrasound sensors "see" as the vehicle drives past other objects. These plots can be analyzed to find open spaces with lengths over threshold values appropriate to the parking spot configuration (1 m for perpendicular parking, 4 m for parallel). A GPS point is extrapolated to the opening from the vehicle's own GPS.

A list of queries in OpenStreetMap is then executed for each of the detected openings. These queries check both that the opening is in a parking area (street or lot), and that the opening is not in some sort of exception case to that parking area (e.g., a bus stop on a street with street parking, or a parking aisle intersection in a parking lot). If an exception query returns true, the opening is marked invalid parking, if a parking area query returns true without any exception cases the opening is marked valid parking, and if no queries return any results the opening is marked unknown. A list of openings can then be passed to the proper PGI system for distribution to or direction of drivers. Figure 4.15 shows an overview flowchart of this process.

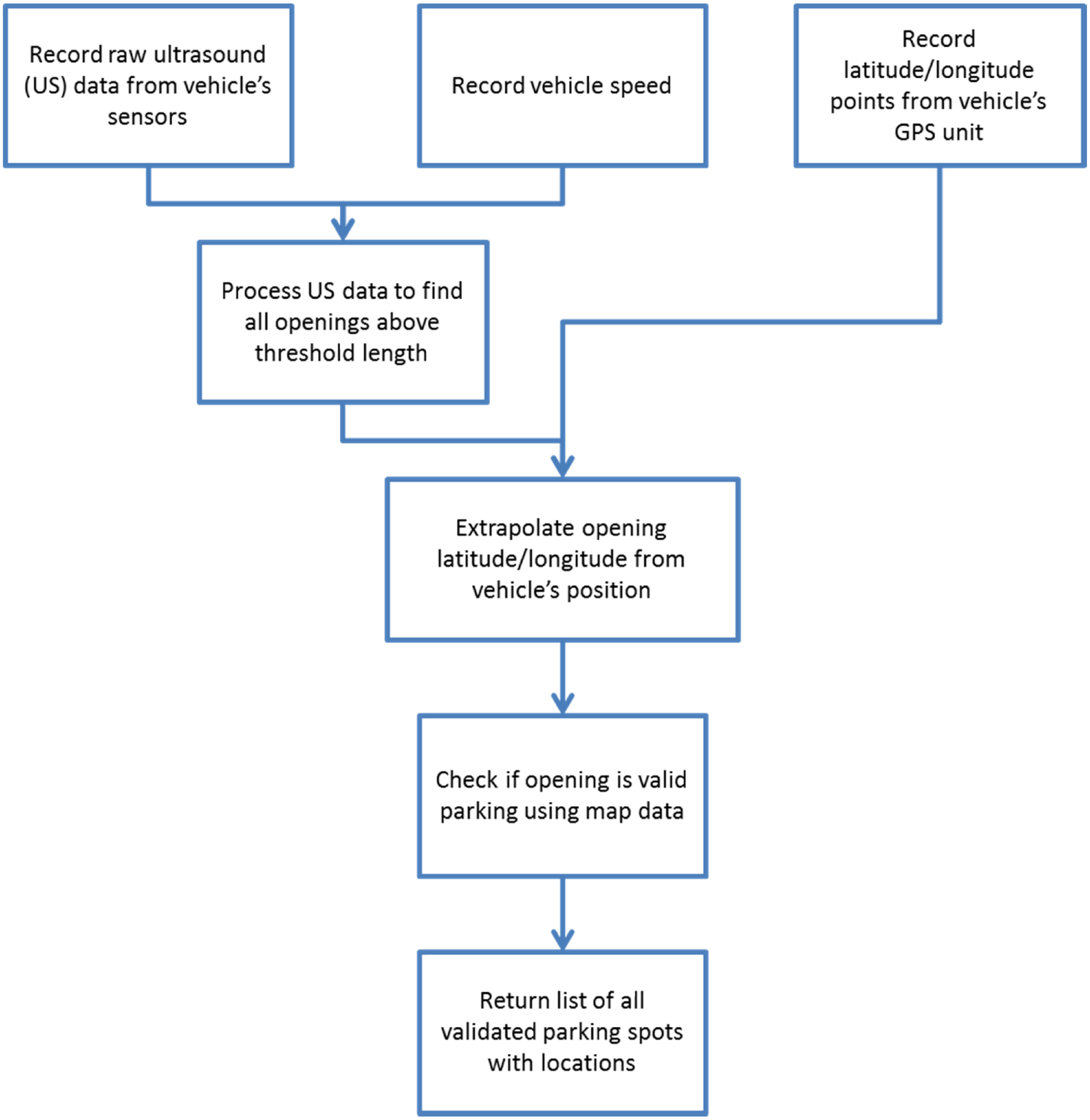

Figure 4.15: High-level flowchart of complete occupancy detection system.

CHAPTER 5

EXPERIMENTAL RESULTS

In this chapter we will present results from of the system in various tests. Results are first presented for the parts of the system working with ultrasound data alone before testing the full system with situational awareness components in various scenarios.

5.1 – Ultrasound Opening Detection, Controlled Tests

The occupancy detection system was tested in several stages. Initially, only the ultrasound sensors and opening detection algorithms were tested in a very controlled manner, for parallel, perpendicular, and angled parking. This initial testing used two parked cars in various positions, which the sensing vehicle drove past at a several different speeds and distances. While testing, a video camera mounted on the window and pointed in the same direction as the ultrasound sensors filmed the passing view to give a record against which to check the ultrasound signals. Testing was conducted with a 2016 Ford Fusion Energi Titanium, although initial algorithm development also made use of a 2013 Ford C-Max Energi.

The two stationary cars were parked in 90 degree (perpendicular), 0 degree (parallel), and 45 positions, the sensing car would drive past a 1, 2, or 3 meters from the bumpers of the parked cars, and the sensing car would travel at either 8 km/h (5 mph) or 16 km/h (10 mph). For each parking configuration and combination of distance and speed, data was recorded 6 times (section 4.2.1 previously referenced a portion of this test when describing width distortion effects). The 90 degree configuration had 3 m (10 ft) of open space between the parked cars, the 0 degree configuration had 7.3 m (24 ft) of open space, and the 45 degree configuration had 3.9 m (12.8

ft) of open space. Figures 5.1, 5.2, and 5.3 show views of three of the parking configuration and distance combinations, taken from the videos recorded from the sensing car as it was driving.

Figure 5.1: Perpendicular parking configuration for controlled testing with sensing car 3 m from parked vehicles.

Figure 5.2: Perpendicular parking configuration for controlled testing with sensing car 1 m from parked vehicles.

Figure 5.3: 45 degree parking configuration for controlled testing, with sensing car 3 m from parked vehicles.

Table 5.1: Average and standard deviation over 6 runs of openings measured between cars perpendicular parked with 3 m spacing.

90 Degree Parking Configuration, 3 m Actual Opening						
Distance from parked vehicles (m)	1		2		3	
Speed (km/h)	8	16	8	16	8	16
Average measured opening (m)	1.66	2.05	1.42	1.70	1.57	0.98
Standard deviation of opening (m)	0.08	0.17	0.29	0.31	0.38	0.38

Table 5.2: Average and standard deviation over 6 runs of openings measured between cars parallel parked with 7.3 m spacing.

0 Degree Parking Configuration, 7.3 m Actual Opening						
Distance from parked vehicles (m)	1		2		3	
Speed (km/h)	8	16	8	16	8	16
Average measured opening (m)	6.41	6.50	6.29	6.26	6.37	6.17
Standard deviation of opening (m)	0.08	0.13	0.16	0.33	0.64	0.52

Table 5.3: Average and standard deviation over 6 runs of openings measured between cars parked at a 45-degree angle with 3.9 m spacing.

45 Degree Parking Configuration, 3.9 m Actual Opening						
Distance from parked vehicles (m)	1		2		3	
Speed (km/h)	8	16	8	16	8	16
Average measured opening (m)	3.60	4.23	4.69	4.23	7.20	7.57
Standard deviation of opening (m)	0.82	0.83	0.46	0.77	0.66	0.53

Table 5.4: Average and standard deviation over 6 runs of openings measured between cars parked at a 60-degree angle with 3.2 m spacing.

60 Degree Parking Configuration, 3.2 m Actual Opening						
Distance from parked vehicles (m)	1		2		3	
Speed (km/h)	8	16	8	16	8	16
Average measured opening (m)	1.85	1.91	1.69	1.77	1.90	2.38
Standard deviation of opening (m)	0.52	0.42	0.58	0.32	0.37	0.32

Tables 5.1, 5.2, 5.3, and 5.4 show the average length and standard deviation of the opening between the cars for each test configuration. The 90, 60, and 0 degree cases generally behaved as expected in this test. As described in section 4.2.1, some width distortion is expected, making the open lengths between parked vehicles appear shorter than they actually are.

Additionally, as the sensing vehicle's speed and distance from the parked vehicles increases, scattering and edge effects become a larger source of run-to-run variation, which can be seen in the increasing standard deviations.

For the 90 degree configuration, all runs taken at 1 and 2 m from the parked vehicles recorded a continuous opening length of at least 1 m which was marked as a possible parking spot by the algorithm. However, one of the runs taken at 3 m and 8 km/h and three of the runs taken at 3 m and 16 km/h experienced sufficient width distortion and edge effects to break the open length up into several smaller lengths under 1 m, as seen in figure 5.4, where a single non-zero point is recorded between the two cars (figure 5.4 also shows a noisy return at the edge of the bumper at 15 m). These smaller openings were between 0.6 and 0.9 m for 3 of the runs. The average value for the open length across the six runs is below 1 m for the 3 m distant, 16 km/h case because in one of the runs the edge effects were particularly large, and the largest single opening was only 0.4 m long. Across all measurement configurations, the average measured opening is 1.56 m, 1.44 m less than the actual opening.

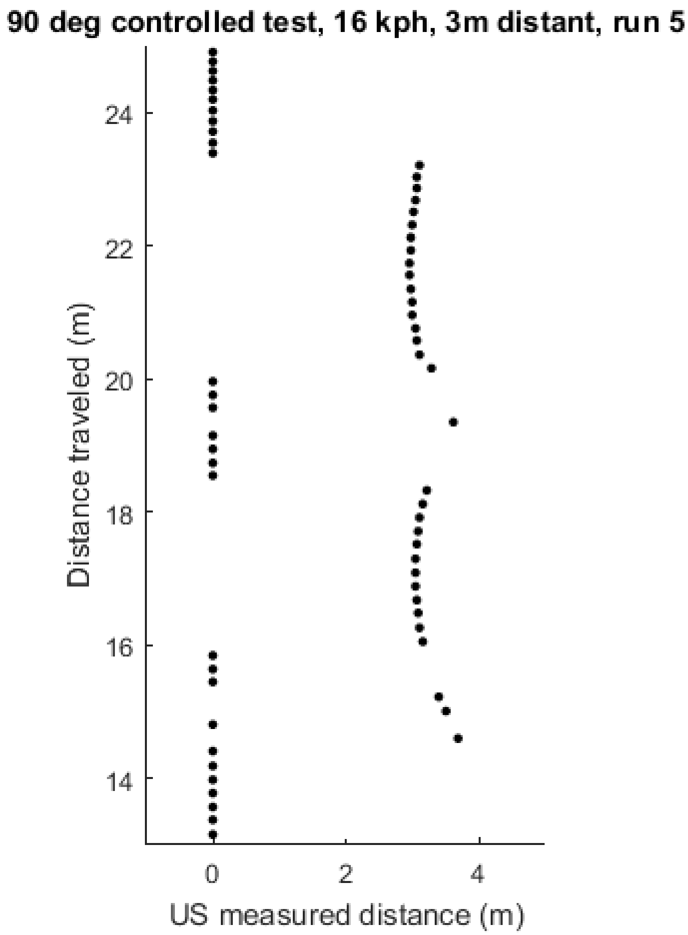

Figure 5.4: Ultrasound trace from controlled 90 degree test, 3 m distant. The opening between two perpendicular-parked cars is broken up by single non-zero point.

The 0 degree cases returned similar results. In all cases, the detected opening was at least 4 m long and thus marked as a possible parallel parking spot by the algorithm. In 6 cases (1 at 2 m and 16 km/h, 2 at 3 m and 5 km/h, and 3 at 3 m and 16 km/h) observed open lengths were below 6 m, with the lowest at 5.36 m. The sub-6 m openings observed at 3 m display similar edge effects as in the 90 degree 3 m cases, but as the overall opening is much larger and the edge effects occur over a comparatively shorter distance, the algorithm has no problem identifying the openings. Across all measurement configurations, the average measured opening is 6.3 m, 1 m less than the actual opening.

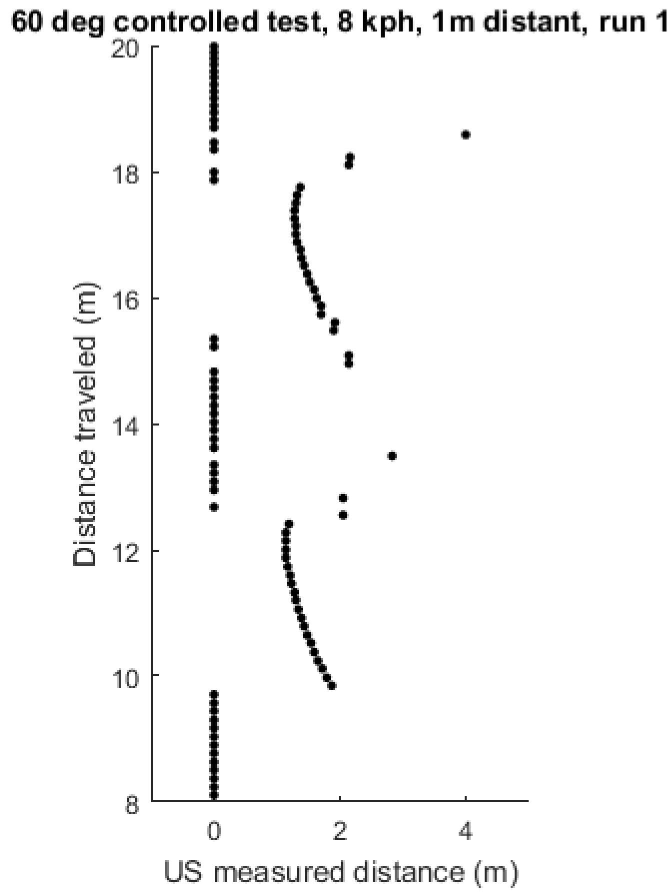

Figure 5.5: Ultrasound trace from controlled 60 degree test, 1 m distant.

The 60 degree case returns results that are also generally as expected. The angling of the bumpers is clear, and there is some additional noise around the corners as was suggested in section 4.2.2, which can be seen in figure 5.5 around 15 m (the points at 13 m and 18 m are consistent with detecting the side of the car for that parking configuration). Standard deviations of the measured opening are somewhat higher than for the 90 degree case. In two cases, both taken at 8 km/h at 2 m distant, the opening is broken up into two smaller openings which are both less than 1 m long and would not be considered as possible parking. Across all measurement configurations, the average measured opening is 1.9 m, 1.3 m less than the actual opening.

The 45 degree case presents more puzzling results. As described in section 4.2.2, we expect more scattering and fewer returned signals from non-planar surfaces when compared to a bumper or the side of a vehicle oriented perpendicularly to the sensors. However, as seen in figures 5.6, 5.7, and 5.8, as distance increases the returned signals become so sparse that at 6 m one of the cars is seen only as two points in the ultrasound trace. This causes the increasing observed open lengths as distance increases, which does not occur in either the 90 degree or 0 degree configuration cases. In 4 of the runs taken at 16 km/h and 3 m distant, one of the cars was represented by only a single point. At least one point was always returned for each parked car, but the minimal number of returned points causes a detected opening that is much larger than the actual opening, such as with the 7 m detected opening shown in figure 5.8.

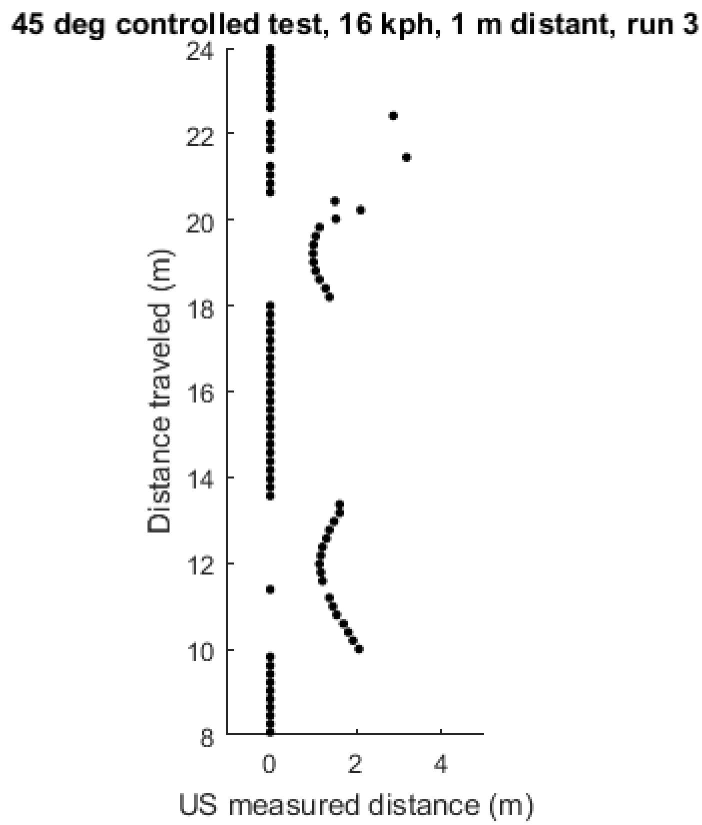

Figure 5.6: Ultrasound trace from controlled 45 degree test, 1 m distant. Scattering is noticeable but two cars are clearly visible, with 4.6 m open length detected between them.

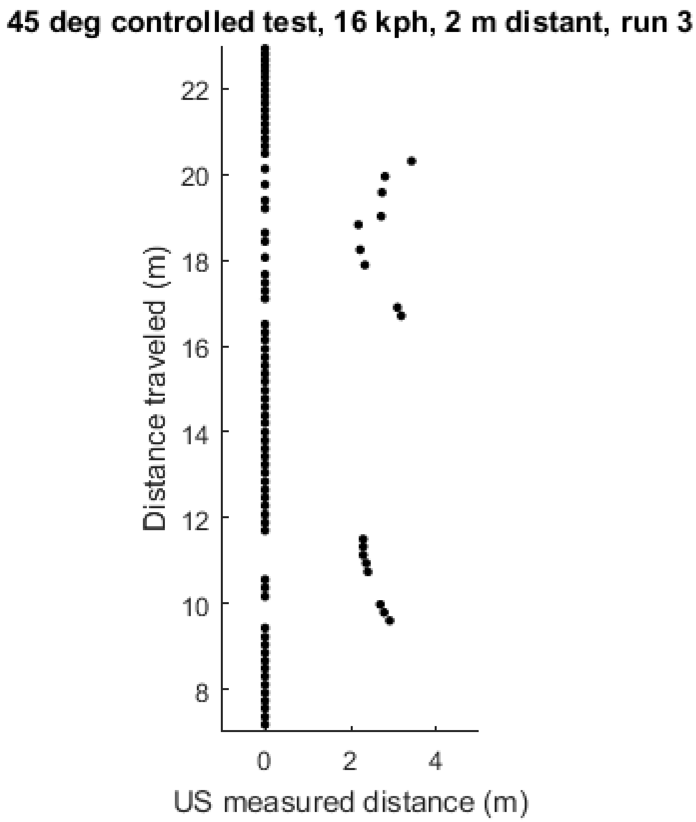

Figure 5.7: Ultrasound trace from controlled 45 degree test, 2 m distant. Parked vehicle signals are more dispersed and shorter than 1 m distant case (figure 5.6) with open length now measuring 5 m.

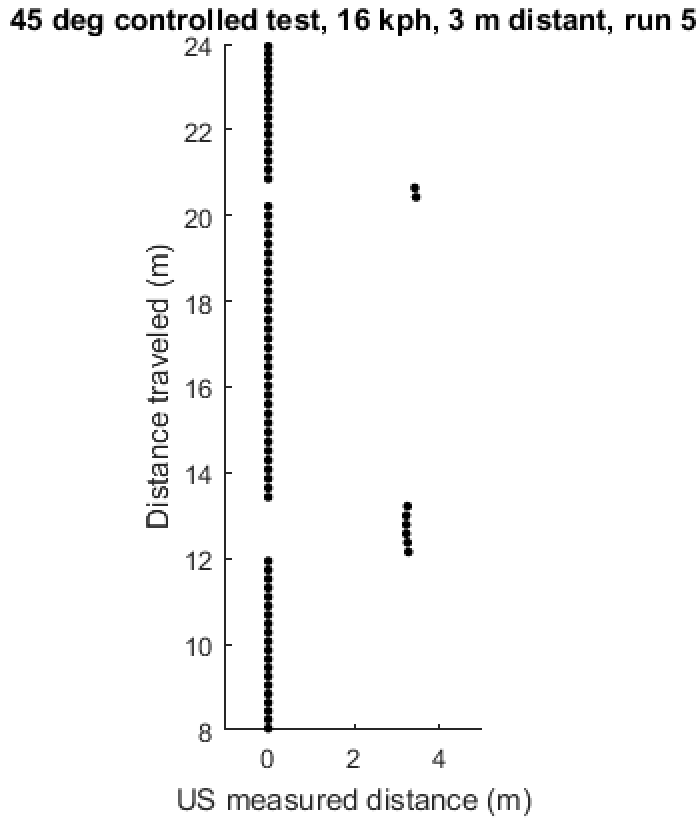

Figure 5.8: Ultrasound trace from controlled 45 degree test, 3 m distant. Minimal return from both parked vehicles, with open length measuring an over-reported 7 m.

These tests indicate that the sensors are generally effective at detecting open parking spaces in perpendicular, parallel, and 60 degree parking configurations in controlled settings. Some degradation of ultrasound signals and corresponding inaccuracies in open space detection does exist as the sensing car moves further away from the parked cars or drives past them at higher speeds. As predicted, width distortion is also noticed, so while opening detection is straightforward opening measurement is usually underreported by 1 to 1.5 m.

Angled parking at 45 degrees, the other parking configurations, is significantly affected by taking measurements at greater distances. Returns from parked vehicles are noticeably sparse at 2 m and almost disappear at 3 m.

5.2 – Full System Testing in Active Parking Areas

We next tested the combined ultrasound data collection and situational awareness system in various parking areas on and around the campus of the Georgia Institute of Technology. For this testing, all detected openings over the threshold length are displayed as colored markers on overhead view images. Overhead images are provided by Microsoft Aerial Provider in Unfolding, a map and visualization library for Java (Nagel, Klerkx, Moere, & Duval, 2013). The color of the marker indicates the validity as parking of the opening, as determined by the situational awareness algorithm. The results are compared to both the raw ultrasound data and to the video recording of the data collection run to check their accuracy.

Figure 5.9 shows the results of one run in an area with curbside parallel parking. 5 open lengths above the threshold are visible in the ultrasound image. All are detected by the algorithm and marked. However, three of the dots are red, signifying invalid parking, and two are green, signifying valid, available parking spots. Looking at the image, the first two red dots are in or near an intersection, while the last is in an area that appears to be marked off by slanted yellow lines. The video confirms that the last red dot is in a bus stop and that there were two open parallel parking spaces where indicated. It also shows a pedestrian walking through the intersection as the sensing car was driving by, breaking one long opening into two shorter ones. This would be considered a successful run: the ultrasound opening detection algorithm found all openings above the threshold length, and the situational awareness algorithm correctly identified which openings should be considered available parking spots and which should not.

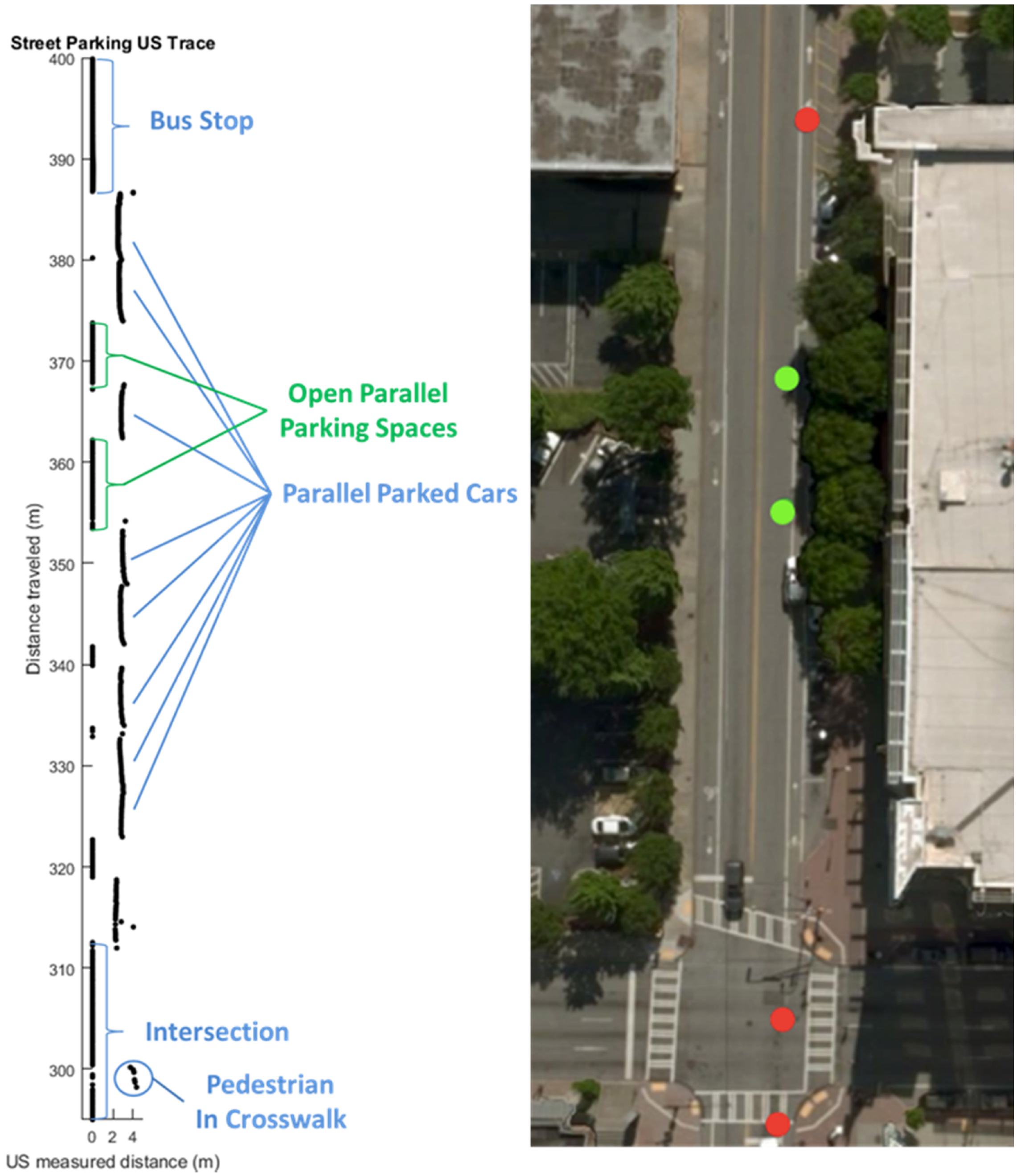

Figure 5.9: Ultrasound trace and aerial view of an area with street parking, with detected openings marked. Background aerial images from Microsoft Aerial Provider in Unfolding (Nagel et al., 2013).

In this section, we will examine runs taken in three different parking configurations to demonstrate the results, strengths, and weaknesses of the open spot detection system in active parking areas.

5.2.1 – Curbside Parking

The image in figure 5.9 is a limited piece of a larger test of the system in an area with curbside parking, the full results of which can be seen in figure 5.10. Red dots mark openings determined to be invalid parking, while green dots mark valid parking. Blue arrows mark the direction of travel of the vehicle along the roads, with solid arrows denoting stretches of road with curbside parking as marked in OpenStreetMap and dashed arrows indicating no such parking is available. The sensing vehicle begins in an area with no curbside parking and then passes several stretches of road with curbside parking as well a parking lot before leaving the area. In all, the vehicle passed through an intersection 9 times and a by bus stop 5 times. All intersections and bus stops were correctly identified and flagged as invalid parking, and a review of the video confirmed that there were three open parking spots, in the locations determined by the algorithm. The openings near the parking lot are identified as either being in intersections or simply in a street, and are marked invalid parking.

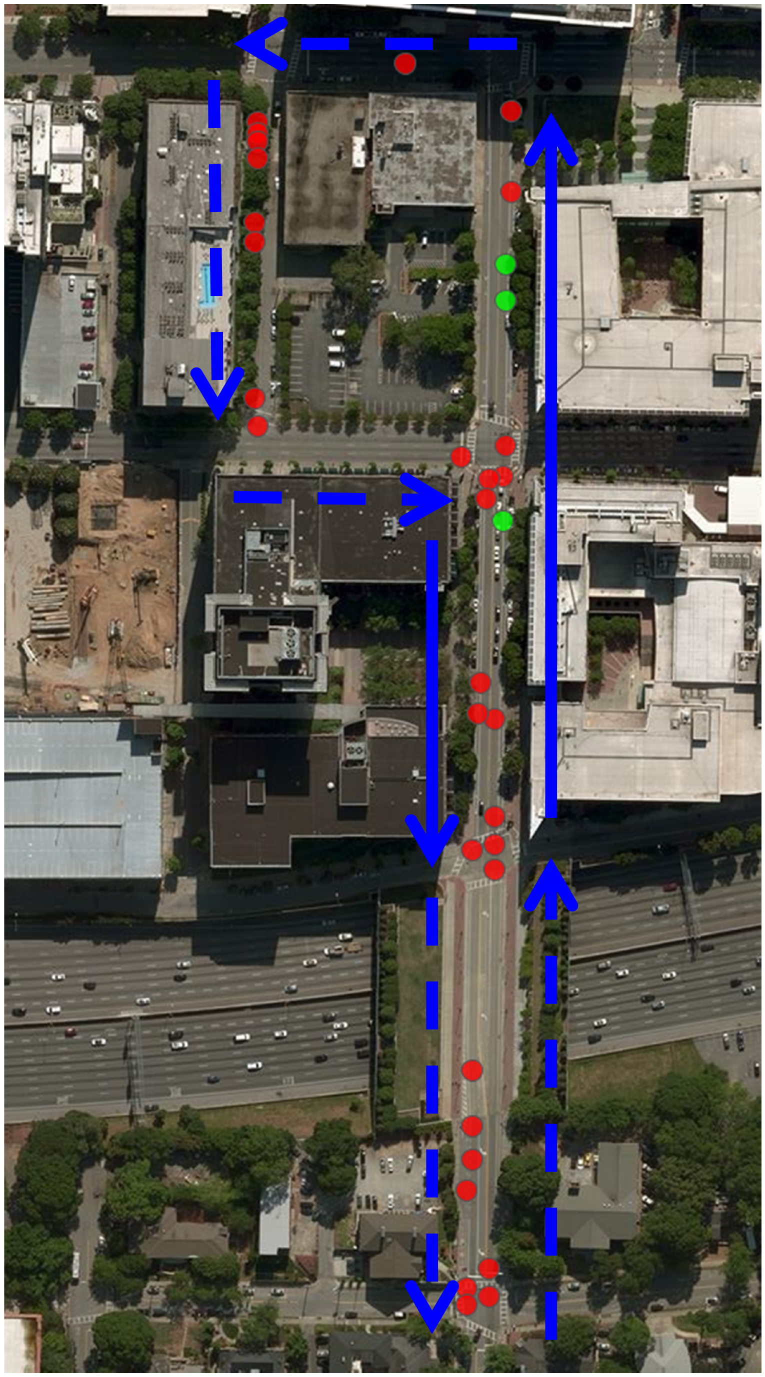

Figure 5.10: Parking occupancy system test in an area with curbside parking, with detected openings and vehicle path marked. Background aerial images from Microsoft Aerial Provider in Unfolding (Nagel et al., 2013).

Using only data collected by native vehicle sensors and a map database, a single vehicle has quickly and accurately determined the number of available curbside parking spots in a busy area in the middle of the day. Non-parking openings seen by the sensors are effectively filtered out and there were no false positive spots reported.

However, this case also highlights one of the main weaknesses of the system. The horizontal street at the top of the image is marked with a dashed line because OSM has no parking indicators for it. In reality, it has a number of parallel parking spots, which were empty in the video recording. This is a successful demonstration of both the ultrasound sensors and the logic and processes behind the situational awareness algorithm, but only a partially successful test of the system as a whole due to the lack of complete and accurate map data.

5.2.2 – Perpendicular Lot Parking

When working with open space detection in parking lots, recall that the false positives initially identified as being of greatest concern were parking aisle intersections, shopping cart returns, handicap parking, and open space for loading areas or pedestrians near storefronts. Of these, we designed the situational awareness algorithm to handle the aisle intersections and any storefront areas, as OSM does not precisely mark handicap spots, and no map that we know of marks shopping cart returns.

An important difference from the previous scenario is that spaces in parking lots are much more densely packed than in curbside parking, and as a result errors caused by GPS drift often have a larger impact. The aisle intersection classification is particularly sensitive to drift, especially for parking spots near the end of aisles. Non-perpendicular aisle intersections may also cause problems if aisles are closer together than would be normal.

Figure 5.11 shows the results of a pass through a large parking lot. The sensing vehicle takes a serpentine path through the lot, starting at the bottom of the image (in front of a Whole Foods) and ending at the top (in front of a Home Depot), with a drive around the left edge of the lot between the two stores. In total the test found 56 openings above the 1 m length threshold. 23 openings were classified as valid parking, and 33 openings were classified as being parking aisle intersections. No openings were classified as being from storefront pedestrian areas or loading zones, although this is because the situational awareness hierarchy choses the parking aisle intersection classification over the storefront classification when both are present.

A review of the video showed that of the 23 openings considered to be valid parking, all were in fact open spaces. The only error in marking open spaces occurred at the two overlaid open markers circled and designated as “1” in figure 5.11: this is in fact only one open space, broken up by a stray non-zero ultrasound data point.

Our system is generally designed to focus more on reducing false positives, even at the expense of false negatives. This is clear when looking at the aisle intersection results: of the 33 detected openings classified this way, 4 are actually valid parking. All occur at the end of aisles of parking aisles, and are circled and designated as “2” in figure 5.11. The two rightmost, nearest the storefront, are actually handicap spots at the beginning of the aisles. The top two and bottom one markers are for openings detected at the ends of aisles. The open spots are the second and third from the end of the aisle for the top two false negatives, while the bottom is actually 4 open spaces at the end of the aisle. The misclassification of these spots is the result of a small amount of GPS drift – a few meters is enough to find two parking aisles within the query radius around the spot and mark the opening an aisle intersection.

This particular lot also provides a good example of the sort of non-perpendicular parking that we were concerned about confusing the aisle intersection query. Figure 5.12 shows an example using the OSM data for this lot of a potential situational awareness check for valid parking that might mistakenly return an aisle intersection. At a 9.1 m aisle intersection search radius, this is avoided, but as shown in appendix A an intersection is returned here for a 10.7 m search radius. Appendix A also shows results for a smaller, 7.6 m search radius.

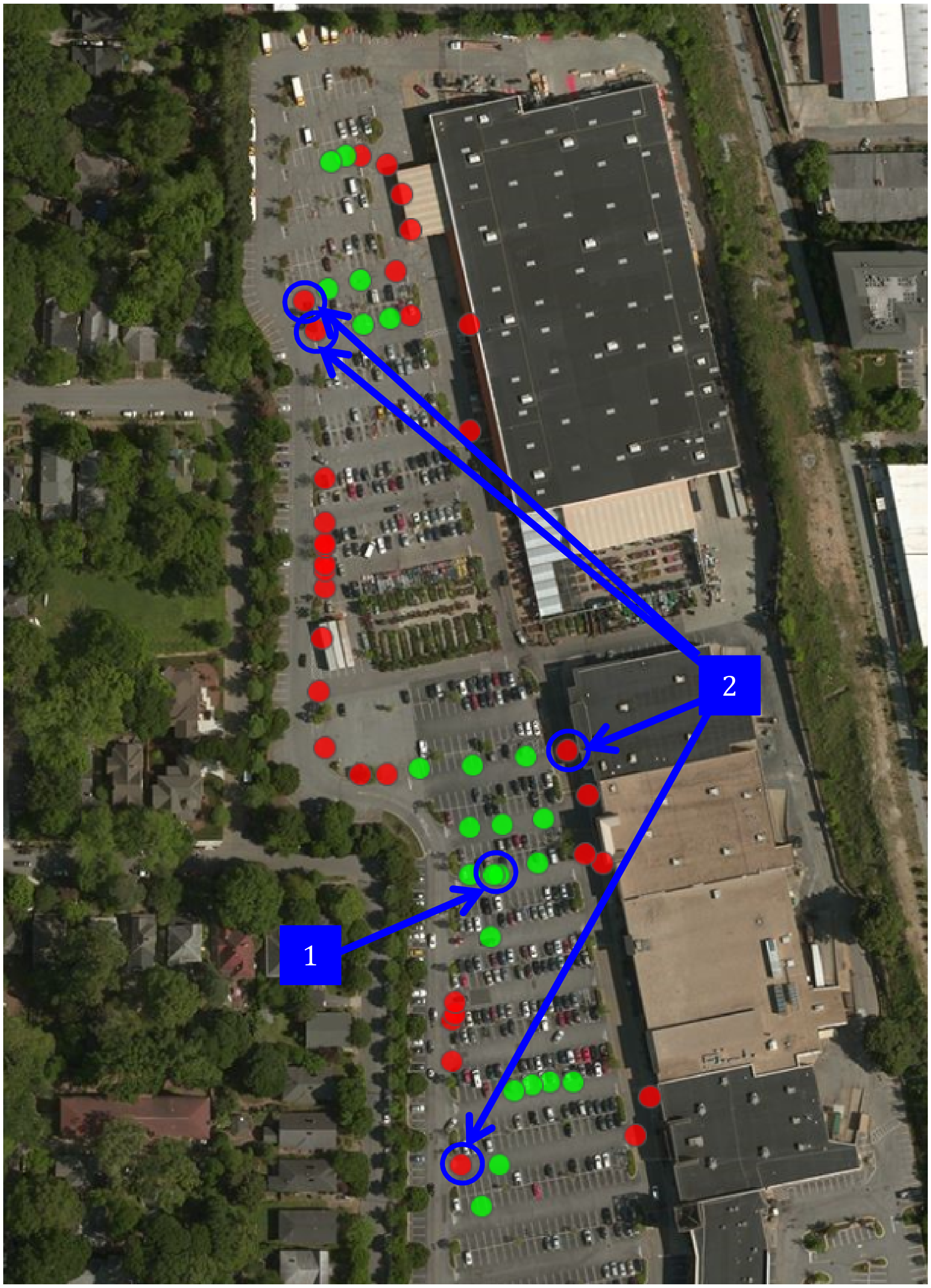

Figure 5.11: Parking occupancy system test in a parking lot, with detected openings marked. Spots marked “1” are ultrasound system errors, and spots marked “2” are false negatives that should be valid parking. Background aerial images from Microsoft Aerial Provider in Unfolding (Nagel et al., 2013).

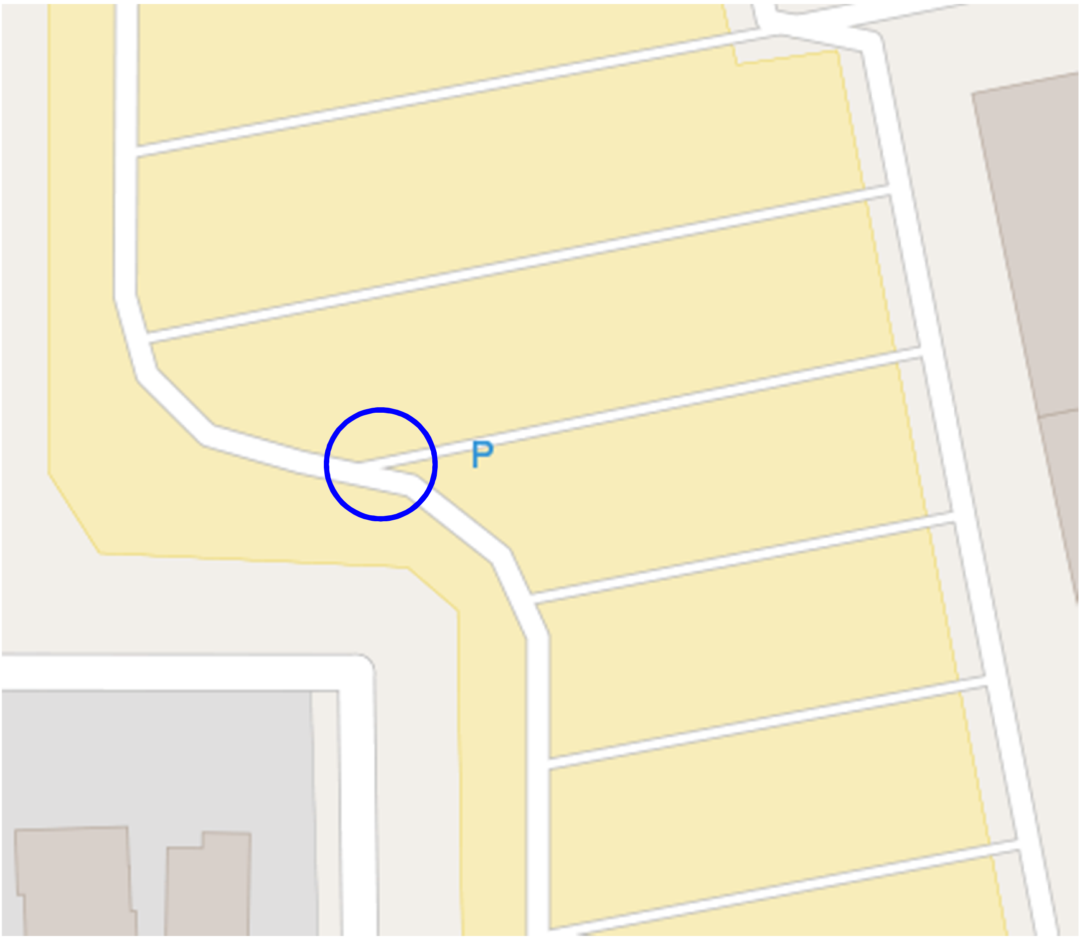

Figure 5.12: Partial OpenStreetMap data for the parking lot in figure 5.11. A non-perpendicular intersection, which is a potential error source for aisle intersection queries, is marked (OpenStreetMap Contributors, 2017).

Our final concern in parking lot scenarios was shopping cart returns not showing up in the ultrasound data and being reported as open parking spots. As seen in 5.12, cart returns were observed in this parking lot, and while returns were sparse they had enough of an echo even at 3.5 m distant to not be observed as openings.

Figure 5.13: Shopping cart return as seen in video and in ultrasound signal.

5.2.3 – Angled Lot Parking

Despite the poor results when trying to detect vehicles parked at an angle in the controlled test, we also tested the complete system in parking lots with angled parking spots. To our surprise, vehicles parked in angled configurations were usually still visible in the ultrasound data in these lots. Figure 5.14 shows the system's output for one of these lots. In this case, GPS drift causing misclassifications at aisle intersection remains an issue, though only for two of the detected openings; the opening marked "1" is an aisle intersection while the opening marked "2" is a valid parking spot.

The larger problem is that 4 of the detected "openings" actually have cars in them or are not complete spaces, marked "3" in figure 5.14. In one case a car is undetected almost entirely, similarly to the controlled tests, and in the other three, the far (most distant from the ultrasound sensor) corner of the bumper is outside the range of the ultrasound sensors, leading to an opening being reported where one should not be. This is shown in figure 5.15 for one of the openings, with a car pulled relatively far forward in its spot creating a 1.1 m opening in the ultrasound trace. The other two false positives are similar cases, with 1.0 and 1.3 m openings. Because these openings are relatively small, a larger minimum opening value around 1.5 m might be effective for solving this issue with angled parking. Determining when to apply this threshold would be difficult, though, because OSM does not mark angled parking lots any differently than perpendicular parking lots.

Additional figures in Appendix A show the effects of varying the aisle intersection search radius.

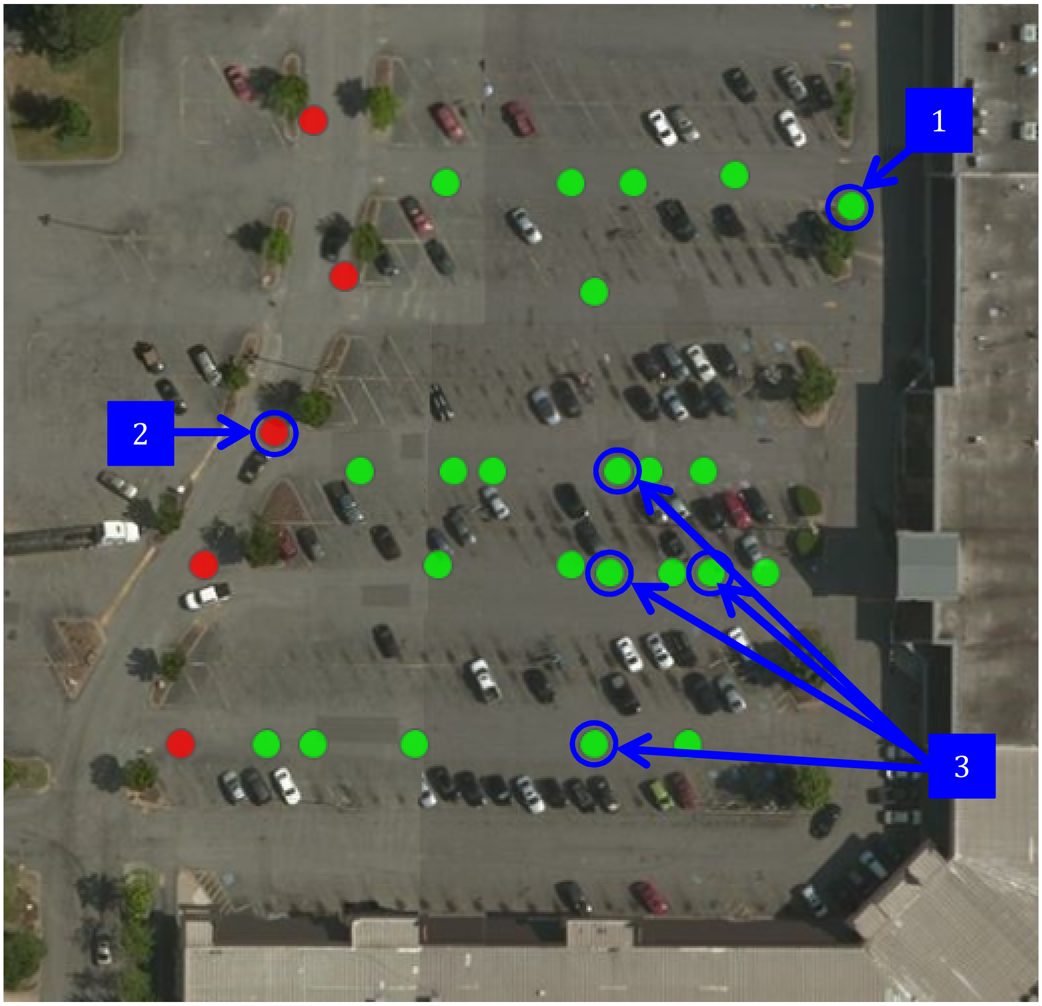

Figure 5.14: Parking occupancy system test in a parking lot with angled parking spots. The spots marked 1 and 2 are aisle intersection misclassifications due to GPS drift errors, while the spots marked 3 are false openings in the ultrasound data. Background aerial images from Microsoft Aerial Provider in Unfolding (Nagel et al., 2013).

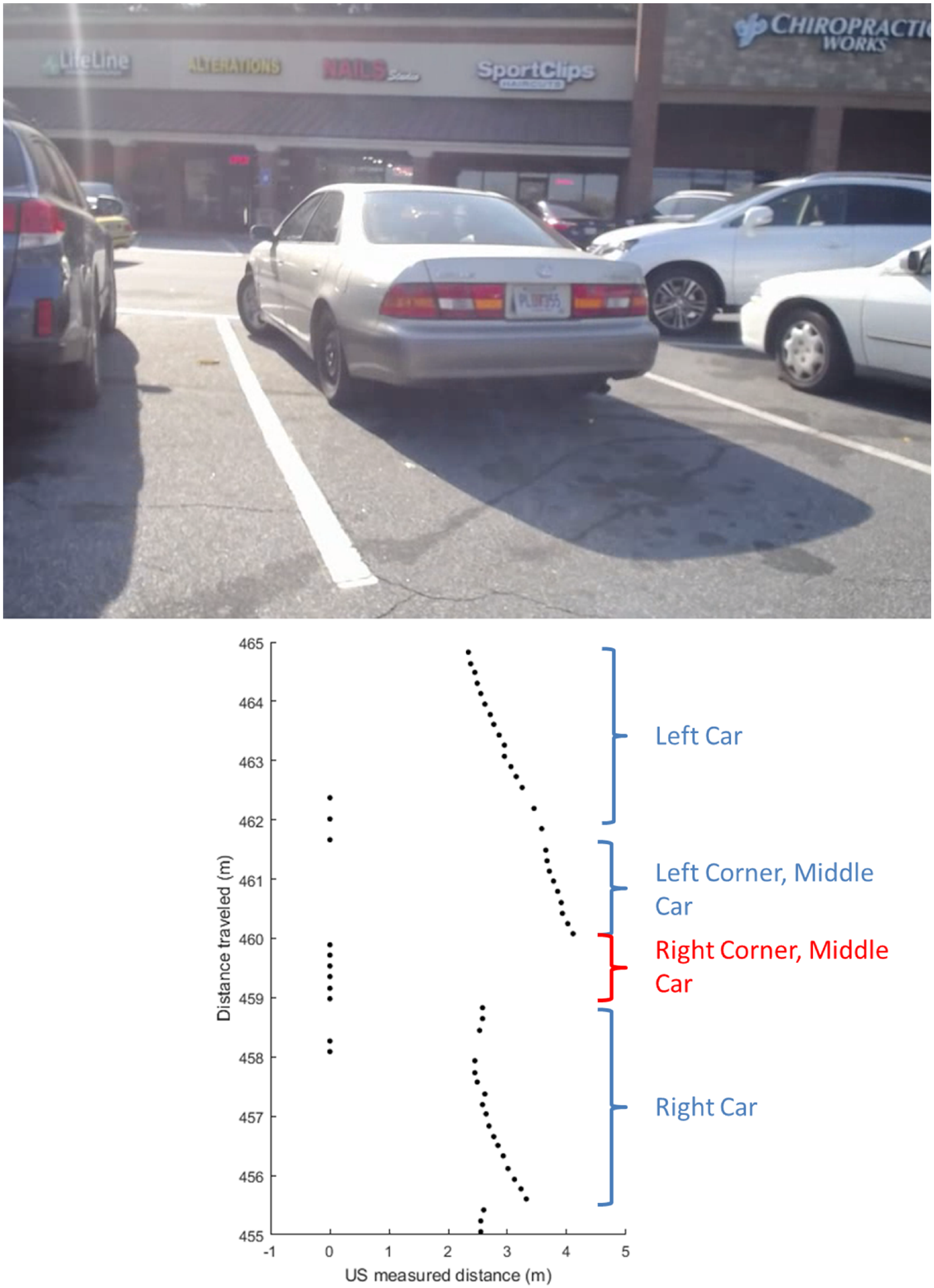

Figure 5.15: Cars parked in an angled parking lot, with ultrasound trace showing disappearing right (most distant) corner of the middle car past 4 m.

Chapter 5 Summary

The occupancy detection system was tested in two pieces, first in a series of controlled tests with the ultrasound sensors alone and then in various active parking lots with the ultrasound sensors and situational awareness algorithms together.

Controlled tests of the ultrasound sensors proceeded as expected for perpendicular and parallel parking. Width distortion as previously described is a noticeable issue, especially for perpendicular parking, reducing the observed opening by as much as 1.6 m from its real length. Edge effects and noise generally become worse, with greater variation between runs as the speed and distance of the sensing vehicle increase. A 1 m minimum opening threshold is appropriate. The parallel parking configuration behaves similarly, though reduction in observed opening due to width distortion is only as much as 1 m. A 4 m minimum opening threshold is appropriate. The angled, 45-degree case is very surprising. Vehicle bumpers have very sparse returns in the ultrasound traces, especially at greater distances. Because of this, openings between parked cars sometimes appear larger than they actually are, in direct contradiction to the expected change from the width distortion effects. It is unclear what an appropriate minimum opening threshold for angled parking should be.

Testing is then conducted for three different parking configurations. A video camera is used to compare to the system's results. For the curbside parking test, a the sensing vehicle drives through an area with mixed street parking spots, bus stops, intersections, and nearby off-street parking lots. The system successfully detects and classifies as parking three available parking spaces. The only error is caused by a gap in OSM data, which fails to indicate street parking on one road and thus returns an incorrect classification for the opening on that road.

When testing in a lot with perpendicular parking, the algorithm successfully identifies 23 openings as being valid parking. There is one ultrasound error that splits an open parking spot up into two smaller spots. Additionally, 4 openings that are valid parking are characterized as parking aisle intersections due to GPS drift at the end of parking aisles (two are handicap spots). No invalid parking spots are reported as valid parking. Shopping cart returns were visible in the ultrasound trace and did not cause any false openings.

The angled parking lot test was considerably more successful than the controlled angled parking test. The majority of the cars were visible in the ultrasound trace, with only one disappearing completely. However, the far corner of the bumper of 3 cars pulled particularly far forward in their spaces was not detected, creating a larger-than-usual gap between the vehicles, which was detected and reported as an opening. This suggests that the minimum opening threshold should be longer for angled parking than for perpendicular parking, but this will require some way to distinguish these parking lot types from each other (OSM does not generally mark orientation for parking lots in its data).

CHAPTER 6

DISCUSSION AND SUMMARY

6.1 – Potential Improvements

The system as described and tested above has several potential sources of error, in both the situational awareness and ultrasound data parts of the system. The situational awareness issues can be further split into map data and GPS accuracy issues.

First, incomplete map data can cause inaccurate classification of detected openings, as with the missing curbside parking data for one of the roads in the curbside parking test. This is an issue that should improve over time, as long as OSM remains a relatively popular project with people willing to dedicate time and effort to its improvement and expansion. More people mapping will cover more areas where data is currently sparse, and more people using the service in well-populated areas will fix errors and improve the maps more rapidly (in fact, the author has made several of his own corrections to data near the Georgia Institute of Technology since beginning this project). If the popularity of OSM slows, or if its data for whatever reason ceases to improve with time, it may become necessary to switch to a different mapping service to maintain data quality. However, it is not clear that any other mapping service currently has OSM's level of granularity for parking data. Interest in parking will likely need to grow larger before other map databases follow suit, though the previously-described historical parking availability functionality recently added to Google Maps (Albertson, 2017) suggests that at least Google may soon incorporate this data. On the whole, though, whether through OSM or another service, we expect map data to improve overall, lessening errors caused by incomplete map data.

Second, even with perfect maps, imperfect GPS location will still be a problem in dense areas such as parking lots where a difference of only a few meters can change a valid parking spot into an aisle intersection. It is unclear how much more accurate we may expect GPS to become in the near future. If it stays roughly at its current accuracy, the decision as to whether false positive or false negative parking spot identifications are less desirable will continue to be an issue when defining search radii for OSM queries. In this project, we prefer to minimize false positives; we believe that failing to advise users of available parking in an area is preferable to directing them to an area that actually has no available parking. We would certainly like to minimize false negatives as much as possible, but more accurate position data will be required for that. Third and related to the second is the issue of irregular parking spot configurations. The search radii for the various tags work well in standard perpendicular lots, but the aisle intersection query in particular may become confused in less neatly laid-out parking lots. If we were more confident in our GPS accuracy, we could reduce these search radii and be more sensitive to the details and particulars of these irregular parking configurations, instead of returning false aisle intersection classifications as happens now. As things are, we again prefer to default to a larger search radius for the invalid parking queries in the interest of minimizing false positives even at the cost of a few more false negatives. A method such as the "environmental fingerprinting" with fixed reference objects used by Mathur et al. may be helpful in mitigating GPS accuracy issues, but further complicates the mapping problem and introduces more complex analysis of ultrasound data (Mathur et al., 2010).

While better map data and GPS accuracy may solve many of the situational awareness issues, there are still occasional problems with the processing of the ultrasound data. The main one of these is the lack of knowledge in OSM regarding perpendicular or angled parking lots. While the sensors do appear to work in parking lots with angled parking, there is clearly a need for a different minimum opening threshold in angled lots, likely around 1.5 m. Without an OSM designation for this different parking type, any angle determination would have to be made only using data immediately available in the sensing vehicle. We have briefly experimented with fitting a first-order curve to the bumpers in the ultrasound data, and then making a determination based off of the slope of that line. However, we have found that due to the occasional noise and scattered returns especially common in angled parking, it is generally better to pick one good fit (e.g., with a high R^2 value between the fit and the data) and make a determination for a larger area based of that one point. The overall process is still complicated and unreliable, though, especially if trying to add in a parallel detection component as well. A simpler solution to this raw distance data problem may simply be a more accurate, longer-ranged type of sensor such as lidar or radar.

6.2 - Implementation

The goal of this system is simply to collect real-time parking occupancy data. The specific application of the data in parking guidance systems is left as an open question. Traditional parking guidance systems are largely sign-based, but more recently with the prevalence of smartphones some such as Ford Motor Company are investigating the development of mobile applications to help find parking.

One aspect that should simplify implementation is more complete integration with the sensing vehicle. In our implementation, all data is collected by and through the vehicle, but the map data and processing happen on a laptop with the full map database loaded on it. Instead of using this external map source, the vehicle's internal guidance map database and processing power could be used. In that case, the only remaining thing necessary would be a data link of some sort to a central server or other cars, but as wireless modems become more prevalent in vehicles even that appears to be less and less of an issue. Complete server-side processing may also be possible; in terms of data size, a JSON format file for one data point containing complete ultrasound, GPS, heading, and vehicle speed data with no vehicle-side processing would be 148 bytes (points are recorded at 25 Hz). The data's simplicity means that initial processing to detect openings is straightforward and quick; the main bottleneck in the system is making repeated queries to the OSM3S server for the situational awareness portion of the algorithm.

We have demonstrated that it is possible to collect all data necessary for this system to function using only the vehicle's native sensors, but it should be possible to go one step further and use the vehicle's own processing power and storage to run the algorithms and situational awareness programs, as well. The result would be a mobile parking occupancy detection system, completely outfitted and equipped from the factory, and working anywhere with sufficient map data with absolutely no input required from the driver.

6.3 – Conclusion

In this thesis, we have motivated the drive for better information on parking occupancy by examining how better informing drivers about available parking can lead to reduced congestion in urban environments. Better informing drivers requires parking guidance system operators to have accurate, timely data of where parking currently is and is not available. Outside of closely controlled areas, keeping track of this parking currently relies on fixed sensors, which can be costly and time-consuming to deploy to all parking spots that need to be monitored.

An alternate solution would be to collect data from a mobile platform, such as other cars driving by the parking spots. In order to do this economically, the occupancy detection should if possible be performed using common sensors already present on vehicles. Ultrasound sensors are both inexpensive and prevalent on current production vehicles. We have implemented an opening-detection system using only data available from a late-model production vehicle's native ultrasound and GPS sensors. In order to ensure that detected openings are valid parking spaces, previous work has suggested that a database with precise locations of all parking spots in an area be created. Instead, we have designed a system to use current map data to check that detected openings are valid parking spots without needing any such parking spot database.

This combined opening detection and parking spot validation system has been implemented and tested in various parking areas around Atlanta, Georgia and has been shown to be an effective way to detect open parking spots both on street and in parking lots.

APPENDIX A

EFFECTS OF VARYING SEARCH RADII

When executing situational awareness queries, the amount of space surrounding detected openings that should be searched for determining parking validity can obviously have a large effect. Here we present results previously shown in figures 5.10 (perpendicular parking) and 5.13 (angled parking) with 7.6 m and 10.7 m (25 ft and 35 ft) aisle intersection search radii rather than the 9.1 m (30 ft) radius described in chapters 4 and 5.

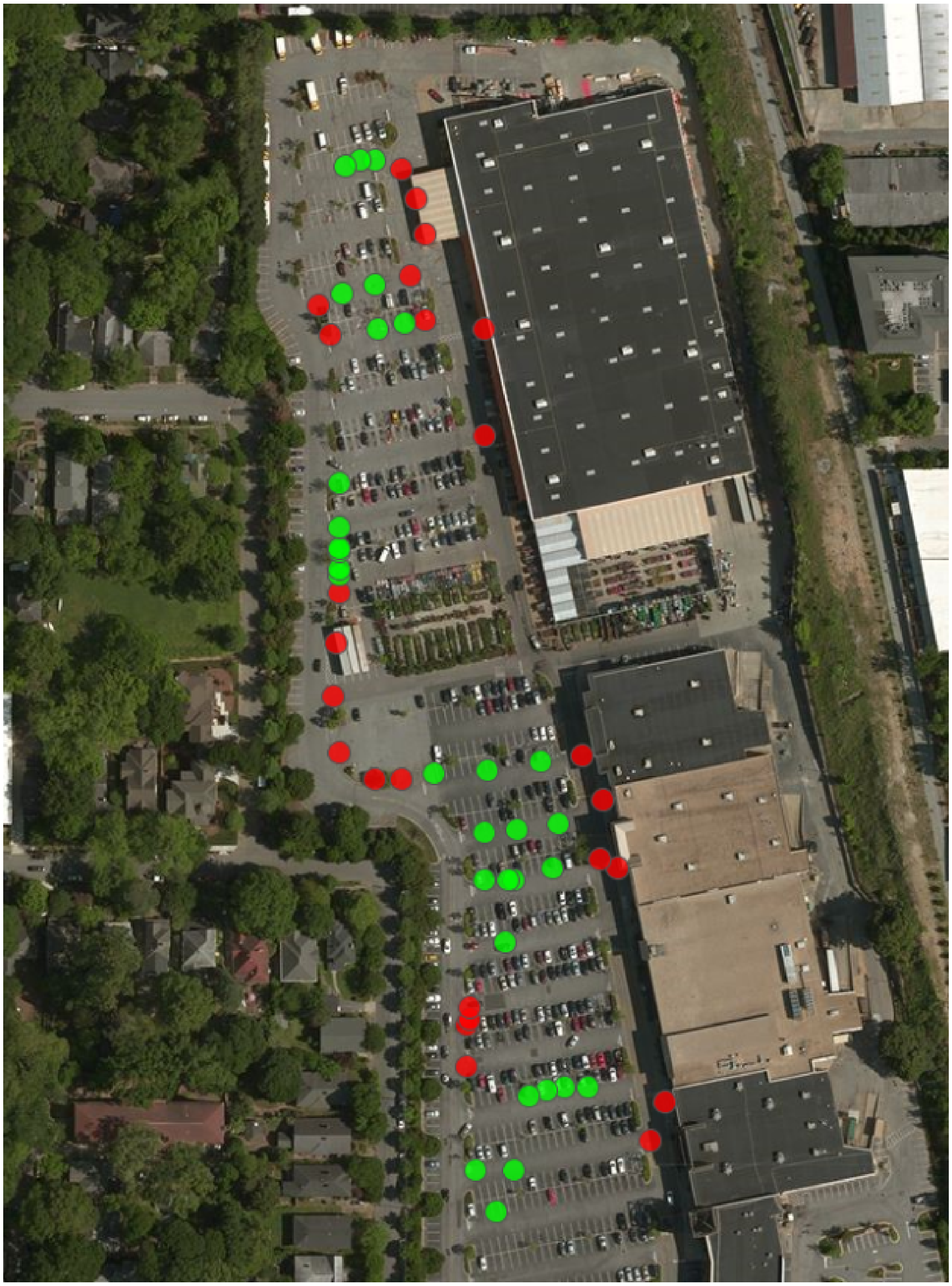

Figure A.1: Perpendicular parking lot results with 7.6 m aisle intersection search radius. One valid opening is corrected while 5 aisle intersections are marked as valid openings when compared to the 9.1 m radius results. (Background aerial images provided by Microsoft Aerial Provider and Nagel et al.)

Figure A.2: Perpendicular parking lot results with 10.7 m aisle intersection search radius. Two additional valid openings are identified as intersections when compared to the 9.1 m radius results. (Background aerial images provided by Microsoft Aerial Provider and Nagel et al.)

Figure A.4: Angled parking lot results with 7.6 m aisle intersection search radius. One additional aisle intersection opening is incorrectly marked valid parking when compared to the 9.1 m radius. (Background aerial images provided by Microsoft Aerial Provider and Nagel et al.)

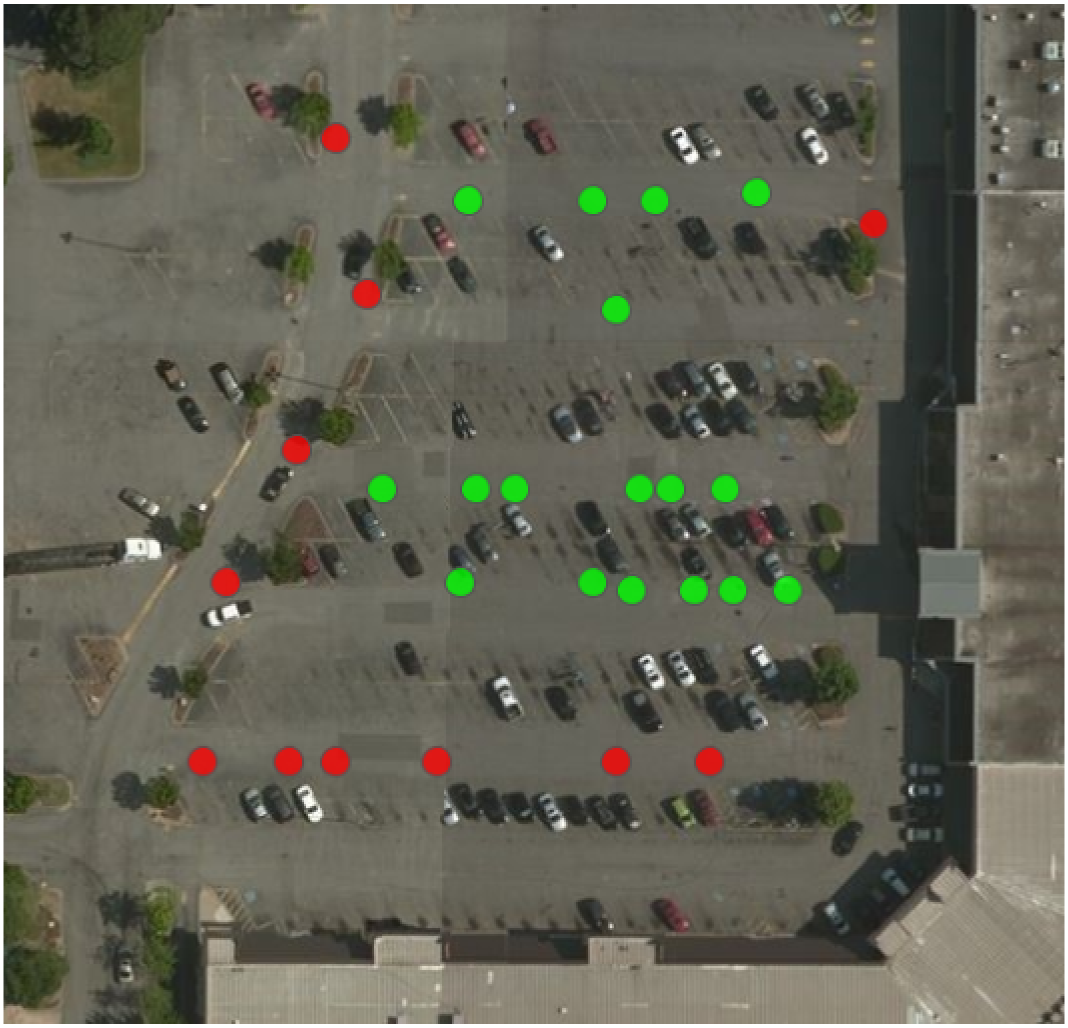

Figure A.4: Angled parking lot results with 10.7 m aisle intersection search radius. One additional aisle intersection opening is correctly while 5 additional openings in a valid parking area are marked as aisle intersections when compared to the 9.1 m radius. (Background aerial images provided by Microsoft Aerial Provider and Nagel et al.)

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